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Monitoring Macronutrients for Eutrophication Control Using the Internet of Things: A Systematic Reviews

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Abstract: Excessive macronutrients—particularly nitrogen (N), phosphorus (P), and carbon (C)—contribute to eutrophication, algal blooms, and water quality degradation in both aquatic and agricultural ecosystems. Traditional nutrient monitoring methods are time-intensive and often lack real-time responsiveness. The Internet of Things (IoT) presents a transformative opportunity for continuous, precise macronutrient monitoring. This systematic review evaluates the global application of IoT technologies in macronutrient monitoring systems, identifying technological trends, challenges, and opportunities for eutrophication control and sustainable nutrient management. The review followed the PRISMA 2020 guidelines and analyzed studies published between 2015 and 2025 across Scopus, Web of Science, and Google Scholar. Inclusion criteria focused on peer-reviewed English-language studies involving real-time IoT-based monitoring of nitrogen, phosphorus, or carbon in agricultural or aquatic settings. A total of 20,251 records were screened, with 82 studies meeting all eligibility criteria. IoT-based macronutrient monitoring research has grown steadily, with statistical modeling used in 43.90% of studies. Thematic emphasis centered on nutrient pollution/removal (52.38%), algal blooms and eutrophication (25.00%), and water quality modeling (11.90%). China (31.70%) and the United States (18.30%) led in research contributions. Despite promising accuracies (up to 98.67%), major gaps remain in reporting hardware specifications, cloud infrastructure, and connectivity protocols, affecting reproducibility. IoT technologies offer substantial potential for enhancing nutrient tracking, precision agriculture, and water quality management. However, adoption is hindered by technical, infrastructural, and reporting barriers, particularly in developing regions. Greater standardization, improved training, and policy integration are needed to realize the full potential of IoT-enabled nutrient monitoring systems.

Keywords: internet of things; macronutrient monitoring; water quality monitoring; agriculture; aquatic ecosystem; sensor accuracy; precision nutrition; statistical modeling

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1. Introduction

Macronutrient regulation, such as carbon(C), nitrogen (N), phosphorus (P), and potassium (K), plays a crucial role in ensuring the health of agricultural crops and aquatic food webs. Water bodies are contaminated by human activities such as solid waste disposal, oil spills, sewage discharge, and air-borne contaminants, posing a significant risk to aquatic food webs and sustainable agriculture (Gehlot et al., 2018). In agricultural practice, nutrient deficiency can lead to reduced crop yield, loss of fertile land, and suboptimal manure or fertilizer practice, thereby affecting food security and balance in the food supply chain (Mahapatro et al., 2024). Meanwhile, excessive nutrient runoff into water bodies causes eutrophication, leading to al-gal blooms, oxygen depletion, and aquatic life loss. Therefore, innovative IoT-based methods of monitoring and controlling water pollution are required (Prabu et al., 2023). Traditional methods to monitoring macronutrient in water quality and agriculture heavily depended on hand testing via sample taking (Stubbs, 2016). The process involved

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sample collection of water or soil to the laboratory for measurement of macronutrient levels, and then used related controlling measures (El-Tohamy et al., 2019). The entire process takes a lot of time, it is costly and less effective with the numerous steps taken to ascertain the pollutants, extent of contaminations, trace the source of the pollutants (Das and Jain, 2017). Long-term, extending knowledge of harmful consequences, e.g., eutrophication, algal bloom, and pollution of water raised a need of innovative solutions for monitoring and precluding water pollution (Ighalo et al., 2021). Such a step marks the ever-increasing role of IoT innovations, where sensors, real-time monitoring systems, auto-mated control and wireless data acquisition mechanism represent a greener way of increasing nutrient utilization, reducing pollution, and maintaining water quality. Water quality in agricultural practices directly affects production of crops yield, soil fertility, and productivity level. Current research towards macro-nutrient sensing is focused on continuous sensing and multi-sensing, and real-time monitoring systems (Ibrahim et al., 2018); this is required since this enables farmers to detect water contamination or macronutrient imbalances in real time. Furthermore, recent innovative technologies such as artificial intelligence (Zulkifli et al., 2022), machine learning (Lalithadevi et al., 2019), deep learning (Thai-Nghe et al., 2020) and fuzzy logic (Nadu, 2020), when combined with IoT systems are referred to as efficient methods for water quality monitoring (Elijah et al., 2018). The key motivation for the use of IoT in macronutrient monitoring is to improve water quality in aquatic systems and increase agricultural production and sustainability. In there, effective management of macronutrients plays an important role in optimizing agricultural production while minimizing environmental effects, such as land degradation and water pollution. However, current use or commercially available real time monitoring systems for macronutrient monitoring on large scale in agriculture does not exist (Postolache et al., 2022). Some of the reasons that contribute to adoption at slower rate include high capital investment needs, technological complexity and resistance to change. Applying IoT systems in macronutrient monitoring requires substantial investment in sensing equipment, network infrastructure and examination tools (Elijah, Rahman, Orikumhi, Leow and Hindia, 2018). In agricultural production it be difficult to justify large scale adoption of IoT systems due to the substantial investment required which can be costly. Moreover, the integration of sensors into the IoT system may require extremely high technical expertise. Inadequate information or capital in some farmers may hinder the adoption of IoT systems, preventing them from becoming widely accepted. The IoT phenomenon has applicability in variety of applications contexts (Zulkifli et al., 2022), such as healthcare and well-being, property and building automation, increasing energy efficiency (Olatinwo and Joubert, 2019), industrial automation, smart metering and smart grid, asset management and logistics, autonomous vehicle and smart transportation, precision precision farming, smart retailing, aquaculture (Boonsong et al., 2020), and monitoring water quality (Oztemel and Gursev, 2020; Zulkifli et al., 2022) . The continuous development of research in macronutrient monitoring, integrated with recent technological advancements in IoT, is a key focus of this study. The aim is to conduct a systematic literature review to examine the latest research trends on macronutrient monitoring. This review offers useful insights into the innovation ecosystem and assists researchers in identifying available solutions for these challenges and issues. A comparative analysis of existing reviews and proposed systematic review is presented in Table 1.

Table 1. Comparative analysis of existing reviews and proposed systematic review.

Ref.	Cites	Year	Contribution	Pros	Cons
Chang et al. (2015)	146	2015	Reviewed remote sensing technologies for water quality monitoring; categorized methods and platforms; provided inversion models and case	Integrative and historical approach; detailed methodological classification; supports ecosystem-based and multiscale water quality management.	Limited citation of applications in developing countries; less focus on recent AI-based models; lacks real-time operational framework.

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Watson et al. (2016)	646	2016	Provided a comprehensive synthesis of nutrient loading, HABs, and hypoxia in Lake Erie, outlining causes, impacts, and adaptive management strategies.	Offered a multidisciplinary analysis across ecology, climatology, and nutrient modeling; highly relevant for policymakers addressing eutrophication.	Region-specific (Lake Erie); challenges in generalizing findings to other aquatic systems.
Glibert et al. (2018)	99	2018	Synthesized almost two decades of global research on harmful algal blooms (HABs), emphasizing ecological drivers, international case studies, and emerging trends through the GEOHAB program.	Comprehensive global perspective; multidisciplinary approach; foundation for future HAB research via Global HAB initiative.	Limited focus on freshwater HABs; some regional disparities in data coverage.
Wurtsbaugh et al. (2019)	986	2019	Provides a broad review of eutrophication impacts, nutrient sources, and algal blooms from freshwater to marine systems, stresses dual nutrient control.	Comprehensive and interdisciplinary; covers freshwater to marine systems; supports policy and management decisions.	General in scope; lacks primary data or modeling; geographic focus mainly on North America and Europe.
Richa et al. (2021)	27	2021	Reviewed the integration of ion-selective electrodes and IoT technologies for nutrient monitoring in hydroponic systems. Focused on sensor performance, ion sensitivity, system calibration, and automation.	Demonstrated the potential of ISEs for real-time monitoring, emphasizing PVC-membrane sensor advantages, IoT-enabled automation, and support for sustainable agriculture	Limited micronutrient sensor development.
Akinnawo. (2023)	264	2023	Reviewed causes, effects, and mitigation of eutrophication; assessed pollutant removal efficiencies, material performance, and advanced technologies like Nano filtration and electrocoagulation.	Provided a comprehensive and comparative review incorporating real-world performance data and integrating multidisciplinary mitigation strategies	Highlighted high technical complexity, limited scalability in developing regions, and the lack of a unified framework for selecting mitigation techniques
Sharma et al. (2024)	5	2024	Conducted a review on AI and IoT applications in plant growth monitoring, covering climatic factors, sensor technologies, data processing, and emerging tools like block chain and robotics.	Integrated a wide range of technologies and case studies, identifying key AI and IoT tools and their agricultural relevance, aiding in the design of intelligent monitoring systems	Lacks original empirical data or field validation.
Sguanci et al. (2024)	8	2024	Reviewed how IoT technologies support nutritional management for patients with chronic neurological cognitive impairments, identifying key applications in monitoring, intervention, and education.	Highlights promising IoT innovations for remote nutritional care, provides a roadmap for future research, and offers insights for healthcare providers.	IoT solutions are in early development, with a lack of standardization and most studies based on small samples and Western contexts

Lan et al. (2024)	31	2024	Provided a comprehensive review of HABs, linking causes to eutrophication from agricultural and urban sources, and evaluating monitoring and treatment methods for effectiveness and sustainability	Offers an integrated view of HABs' causes and responses, with a detailed analysis of global patterns and highlights technological advancements in monitoring and mitigation	Lacks new empirical data or modeling, with generalizations that may overlook regional variability and a descriptive approach without deep comparative analysis of interventions.
Bai et al. (2025)	2	2024	Conducted a meta-analysis on 115 studies to evaluate nitrogen and phosphorus removal efficiency in ecological ditches, analyzing factors like plant type, materials, temperature, and hydraulic retention time.	Offers a comprehensive synthesis across multiple variables and vegetation setups, useful for designing agricultural pollution mitigation strategies	Limited geographic diversity (mostly from China), lacks real-time or operational field-testing data, and does not fully address potential variability due to local climate or soil.
Proposed systematic review			Reviews current applications of Internet of Things (IoT) technologies in monitoring macronutrients (nitrogen, phosphorus, potassium) in agricultural and environmental systems.	Identifies technological advancements, integration potential with real-time data analytics, and enhanced precision in nutrient monitoring and management.	Limited scalability in rural or underdeveloped regions, concerns over data privacy, and high initial costs for deployment and maintenance of IoT infrastructure.

1.1. Research Questions

This review investigates the application of IoT technologies in macronutrient monitoring by assessing current implementations, identifying technical and operational limitations, and exploring opportunities for enhanced nutrient management. The following research questions guided the review:

- What IoT technologies are currently used to monitor nitrogen, phosphorus, and carbon in agricultural and aquatic environments?
- What are the key technical, financial, and infrastructural barriers to successful implementation of IoT-based nutrient monitoring systems?
- How do limitations in reporting, system accuracy, and connectivity affect the performance and scalability of these systems?
- What potential exists for integrating IoT with advanced technologies such as AI, cloud computing, and machine learning to improve nutrient monitoring?
- What factors influence user adoption and long-term sustainability of IoT-enabled macronutrient monitoring solutions, especially in low-resource settings?

1.2. Research Rationale

The fast-paced progress of IoT technologies reshapes traditional methods when handling data acquisition and analysis for health care and agricultural and nutritional domains. The monitoring of macronutrients emerges as a vital operational field which presents substantial advantages for both human healthcare improvement and agricultural production efficiency and nutrition individualization. The technology promises real-time accurate automation of macronutrient tracking yet major operational and technical obstacles block their general use and success implementation.

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Multiple issues make it difficult to implement IoT systems through data reliability problems and privacy threats and standardization requirements and device interconnection boundaries. The implementation of IoT solutions becomes complicated in practical environments because of resource restrictions as well as user unawareness and insufficient infrastructure. The barriers to adopt IoT-based monitoring for macronutrients do not prevent the potential benefits of innovative solutions for better results. A systematic method is used by this review to investigate present IoT applications in macronutrient monitoring by identifying key challenges together with available untapped prospects. The research analyzes literature from 2015 through 2025 to find IoT technology deficits and successful practices and developing trends which will support upcoming scientific investigations while guiding decision-makers in IoT technology adoption. Such an extensive assessment works to boost overall understanding while supporting strategic growth within IoT-based macronutrient tracking research.

1.3. Research Objectives

The primary objective of this systematic review is to evaluate how Internet of Things (IoT) technologies are being applied to monitor macronutrients—specifically nitrogen (N), phosphorus (P), and carbon (C)—in agricultural and aquatic systems. The review aims to:

- Identify current IoT practices and technologies used in nutrient monitoring;
- Examine implementation barriers such as high costs, limited reporting of system architecture, and lack of standardization;
- Analyze trends in sensor use, connectivity, cloud integration, and data processing techniques;
- Assess how IoT-enabled systems contribute to improving nutrient tracking accuracy and supporting real-time decision-making;

Synthesizing findings from 82 peer-reviewed studies (2015–2025), this review contributes to a clearer understanding of the state of IoT adoption in macronutrient monitoring and offers practical guidance for improving deployment in both developed and developing regions.

1.4. Research Contributions

This review provides a systematic evaluation of 82 studies on the use of IoT technologies for monitoring nitrogen, phosphorus, and carbon in agricultural and aquatic environments. The key contributions are:

- Identified how IoT is used for macronutrient monitoring, with a focus on eutrophication control, water quality, and precision agriculture.
- Found that 75% of studies did not report microcontroller use, and 70.24% omitted connectivity details, highlighting a lack of system transparency.
- Categorized IoT systems into basic (sensor-only), intermediate (cloud-connected), and advanced (AI-integrated) stages based on reported implementations.
- Showed that 42.86% of studies used statistical models, with some reporting accuracies up to 98.67%, despite many lacking performance metrics.
- Provided guidance on standardization, scalability, and policy relevance to support improved implementation of IoT-based nutrient monitoring systems.

1.5. Research Novelty

This review offers a novel contribution by systematically analyzing the use of IoT technologies for monitoring nitrogen, phosphorus, and carbon—an area that remains sparsely addressed in the existing literature. While IoT applications in agriculture and water management are widely reported, few studies examine their role in macronutrient tracking. This work addresses that gap by identifying key challenges such as poor reporting of system components, limited use of advanced analytics, and barriers to adoption in low-resource settings. It also introduces a practical categorization of IoT adoption levels observed in the literature, providing a clearer understanding of the current maturity and limitations of IoT-based nutrient monitoring.

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2. Materials and Methods

2.1. Eligibility Criteria

A systematic review of all peer-reviewed and published studies relevant to the application of IoT technologies for monitoring macronutrients was conducted for evaluation. Only research articles published in English between 2015 and 2025 were considered eligible for inclusion. The researcher applied stringent criteria to select studies dedicated to IoT-based macronutrient level measurement and analysis of proteins and carbohydrates and fats. Research about overall health monitoring systems that failed to mention macronutrients was excluded from consideration. Tight selection criteria included both research articles that presented valid empirical frameworks and methodology to guarantee the scientific quality of the included studies. The approach used mirrors those found in recent IoT-related reviews across energy and SME contexts (Msane et al., 2024; Molete et al., 2025; Kgakatsi et al., 2024). Table 2 summarizes the admission and rejection rules for articles incorporated in this assessment.

Table 2. Proposed Inclusion and Exclusion Criteria.

Criteria	Inclusion	Exclusion
Topic	Research papers focusing on real-time monitoring of macronutrients (Carbon, Nitrogen, Phosphorus) using IoT-based sensors.	Research papers not focusing on real-time monitoring of macronutrients or those studying unrelated water quality parameters.
Research Framework	Research articles with a clear methodology linking IoT technology to macronutrient monitoring	Articles without empirical research frameworks or relevant methodologies
Language	Research papers must be written in English.	Research papers published in languages other than English.
Period	Articles between 2015 to 2025	Articles outside 2015 and 2025

2.2. Information Sources

An organized research strategy involving different respected online databases enabled the identification of suitable research studies. This research used Scopus, Web of Science and Google Scholar databases because these platforms offer extensive coverage of peer-reviewed technology health science and engineering research (Dladla & Thango, 2025; Thobejane & Thango, 2024). Several targeted keywords including “Internet of Things” and “IoT” and their variations with both “macronutrients” and “nutrient monitoring” together with “food consumption” were used in the search. The researchers conducted extensive searches in each database to retrieve all qualified studies together with appropriate documents from informal literature and conference proceedings. The last search round occurred in April 2025 along with reference list verification from identified articles to guarantee data collection completeness. Duplicate records were carefully removed to avoid repetition and bias in the selection of studies.

2.3. Search Strategy

The research adhered to an organized approach that followed methods outlined in PRISMA 2020 guideline (Khanyi et al., 2024). The research utilized the major academic search engines Google Scholar, Scopus, and Web of Science for database research. Specific keyword bundles served as the foundation to locate academic papers regarding macronutrient monitoring together with water quality assessment. The Web of Science query contained these terms for the search: ("nutrient management" OR "nutrient removal" OR "aquatic systems") AND ("eutrophication" OR "algal bloom") AND ("phosphorus" OR "nitrogen" OR "carbon" OR "dissolved carbon") OR ("IoT" OR "Internet of Things") AND ("water quality" OR "water monitoring"). The search engine at Scopus implemented (nutrient management OR nutrient removal) AND (eutrophication OR algal bloom)

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AND (phosphorus OR nitrogen) AND IoT as its search keywords. The Google Scholar search employed "nutrient management" OR "nutrient removal" as its search criteria along with "eutrophication" or "algal bloom" and included "phosphorus" OR "nitrogen". The applied search yielded a total of 2,743 articles on Web of Science and 708 articles on Scopus alongside 16,800 articles on Google Scholar. The research utilized information from scientific papers released from 2015 to 2025 for maintaining contemporary relevance throughout the review. The selection of unique timeframes by researchers served to prevent the retrieval of duplicate information. The authors performed methodical steps for filtering out high-quality relevant studies that emerged after completing the retrieval phase, as recommended in previous data-intensive systematic reviews (Pingilili et al., 2025; Kgakatsi et al., 2024). The data source, search string and number of results found are presented in Table 3.

Table 3. Data source, search string and number of results found.

Source	Search string	Results
Web of science	("nutrient management" OR "nutrient removal" OR "aquatic systems") AND ("eutrophication" OR "algal bloom") AND ("phosphorus" OR "nitrogen" OR "carbon" OR "dissolved carbon") OR ("IoT" OR "Internet of Things") AND ("water quality" OR "water monitoring")	2743
Scopus	(nutrient management OR nutrient removal) AND (eutrophication OR algal bloom) AND (phosphorus OR nitrogen) AND IoT. For Google Scholar, the search included ("nutrient management" OR "nutrient removal") AND ("eutrophication" OR "algal bloom") AND ("phosphorus" OR "nitrogen")	708
Google Scholar	("nutrient management" OR "nutrient removal") AND ("eutrophication" OR "algal bloom") AND ("phosphorus" OR "nitrogen")	16800

2.4. Selection Process

Four researchers initially screened the first 80 records' titles and abstracts obtained from the search independently. The researchers conducted their selection independently for all records pertaining to their specified eligibility requirements and research aims. The four researchers met for comparison of their selections following their initial independent reviews. A discussion session among the researchers maintained clear understanding of the selection criteria which resulted in improved consistency throughout the remaining assessment stages. Each of the four researchers individually screened all remaining titles and abstracts after the calibration process. Judgment was rendered on studies by individual assessment to achieve both fairness and minimize biased results. The researchers openly exchanged their reasons for disagreements before reaching consensus on whether the study would continue to full-text screening. All four reviewers conducted an independent examination of full-text articles to determine eligibility during the last phase of evaluation. Group discussions served as the method to solve any disagreement that arose between researchers. Such a methodical multi-step screening assured the selection process remained open and dependable in support of research aims (Thobejane & Thango, 2024; Chabalala et al., 2024). The Method for selection process employed are presented in Table 4.

Table 4. Method for selection process.

Stage	Action	Researchers
Initial Screening	First 80 records independently reviewed.	K, NC, OA and KP
Discussion of Calibration	Discussed and resolved early disagreements	K, NC, OA and KP

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Independent Title/Abstract Screening	Remaining records screened individually	K, NC, OA and KP
Full Text Review	Independently checked full text articles for eligibility	K, NC, OA and KP
Final Consensus Meeting	Resolve conflicts through discussions	K, NC, OA and KP

2.5. Data Collection Process

The researchers followed the eligibility screening to participate in the data collection procedures. Researchers utilized a shared Excel platform for accurately documenting essential observations from chosen studies. Each researcher examined separately their designated studies to gather relevant data that included information about IoT systems, macronutrient monitoring practices, used technologies and study scenarios alongside documented challenges. The researchers cross-validated their extracted details about study summaries with an additional team member to confirm precision. Team members discussed findings and settled disagreements by coming to agreement during discussions of unclear interpretation and inconsistencies. This collaborative cross-validation strategy was successfully implemented in previous reviews on transformer condition monitoring and SME data systems (Msane et al., 2024; Ngcobo et al., 2024). The multitier methodology kept the research dataset solid while enabling quality preservation before moving into elaborate stage aggregating in the next phase. The Data collection process is illustrated in Figure 1.

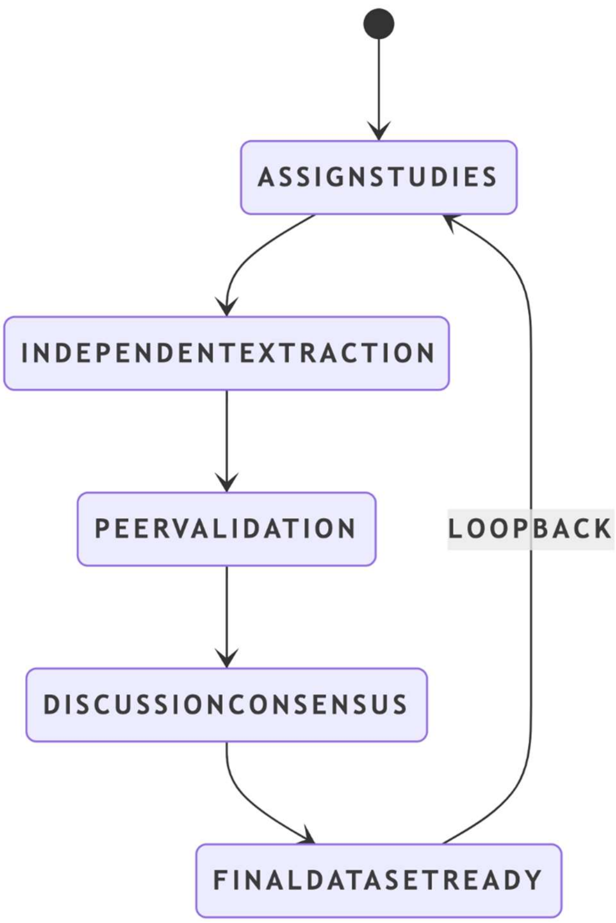

Figure 1. Data collection process.

2.6. Data Items

This assessment followed a systematic approach to collect specific data points that allowed for study analysis as well as comparison of IoT applications in macronutrient monitoring. Both technological and contextual study features were recorded through specific data items that enabled

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effective analysis for synthesis. Data were extracted to reflect critical aspects such as the type of macronutrients monitored (carbon, nitrogen, phosphorus, potassium), the sensing technologies used (sensors), the application environment (agriculture fields or aquatic ecosystems), and the connectivity infrastructure applied (Wi-Fi).Additional elements collected included study outcomes, such as improvement in monitoring efficiency or water quality, major challenges encountered, such as sensor drift or high costs, and any recommendations provided by the authors for future research. The research collected details about manual and machine-learning-driven data processing together with cloud-based data management when such information became available. The gathered data received spreadsheet organization to categorize studies by technology category and result achievements. (Molete et al., 2025; Pingilili et al., 2025).

A methodical organizational system enabled researchers to classify research data while identifying recurring patterns and analyzing system methods and identifying obstacles and potential developments in nutrient monitoring via Internet of Things technology.

2.6.1. Data Collection Method

A straightforward procedure was implemented to collect data used for this review. The Excel table included essential headings which related to the studies. The procedure required the following sequential method: (1) An Excel sheet was prepared with columns such as Paper ID, Paper Title, Citations, Year Published, Research Type, Online Repository, Journal Name, Country of Authors, Water Source, Investigated Water Aspect, Nitrogen (N), Phosphorus (P), Carbon, Sensors Used, Microcontroller, Connection Type, Cloud Used, Software Used, Model Evaluation Metrics, Accuracy, Key Findings, IEEE Reference Format, and Link. (Dladla & Thango 2025; Msaneet al.,2024). (2) Before starting full extraction, reviewers were given time to study and practice the meaning of each heading. Sample papers were used to ensure a common understanding among the team (Khanyi et al., 2024; Pingilili et al., 2025). (3) Each assigned paper was independently read by the reviewer. They extracted the necessary details and entered them into the spreadsheet. Where differences were found, group discussions were held to reach consensus (Ngcobo et al., 2024; Molete et al., 2025). The data collection methods used in this study is illustrated in Figure 2.

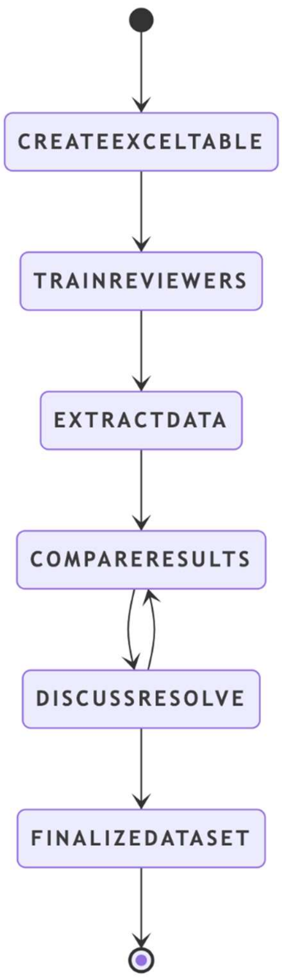

Figure 2. Data collection methods.

2.6.2. Definition of Collected Data Variables

In addition to the outcomes related to nutrient monitoring (nitrogen, phosphorus, and carbon), we systematically extracted a broad set of variables to better understand the context and technological approaches of each study. These variables were defined in advance to ensure consistency during the data extraction process. (Kgakatsi et al., 2024; Thobejane & Thango, 2024). The following data items were collected. The Fields description for the table used to collect data is tabulated in Table 5.

Table 5. Fields description for the table used to collect data.

Field	Definition
Paper ID	An internal identifier assigned to each paper for organization.
Paper Title	Full title of the study.
Citations	Number of citations the study had received (at time of collection) to assess impact
Year	Publication year to identify trends over time.
Research Type	Categorization as a Journal Paper, Conference Paper, Book Chapter, Dissertation, or Thesis.
Online repository	

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	Source database used to retrieve the study (Google Scholar, SCOPUS, or Web of Science).
Country of Authors	
	Country or countries affiliated with the authors, for geographical trend analysis.
Water source	
Investigated water aspect	Specific water body or source investigated (e.g., rivers, lakes, wastewater).
Macronutrients	The aspect of water quality that was the focus (e.g., nutrient concentration, eutrophication monitoring).
Sensor	The aspect of water quality that was the focus (e.g., nutrient concentration, eutrophication monitoring).
Microcontroller	
	Types of sensors or sensing technology applied
Connection type	
	Type of microcontroller used
Cloud used	
	Communication protocols employed (e.g., Wi-Fi)
Software used	Whether and which cloud platforms were utilized for data storage or processing (e.g., AWS, Azure, Google Cloud).
Software used	Any software tools mentioned for data analysis, visualization, or system development.
Model evaluation metrics	Any software tools mentioned for data analysis, visualization, or system development.
Accuracy	
Key findings	Metrics used to evaluate predictive or monitoring models (e.g., RMSE, R^2, MAE).
IEEE Reference Format Link	Reported accuracy values associated with the models
	Major conclusions or innovations reported by the study
	Complete reference citation for standardized referencing
	Direct access link to the paper or its repository record

2.7. Study Risk of Bias Assessment

The narrative review method evaluated bias risks in the evaluated studies for this assessment. Professionals reviewed all studies by hand using three core aspects. The first analysis involved verifying that research included comprehensive reporting about its objectives and both IoT setup processes and all nutrient measurement outcomes. Secondly, we evaluated real-world applicability through verifying the IoT systems ran tests in natural agricultural fields or aquatic environments instead of laboratory settings alone. Transparency analysis evaluated the study by identifying and discussing every limitation and weakness and areas for improvement which required addressing. Studies received one of three assessments which included comprehensive reporting and partial reporting and limited reporting. The judges disseminated opinions until they achieved mutual agreement about their ratings (Molete et al., 2025). The study risk bias assessment used in this study is illustrated in Figure 3.

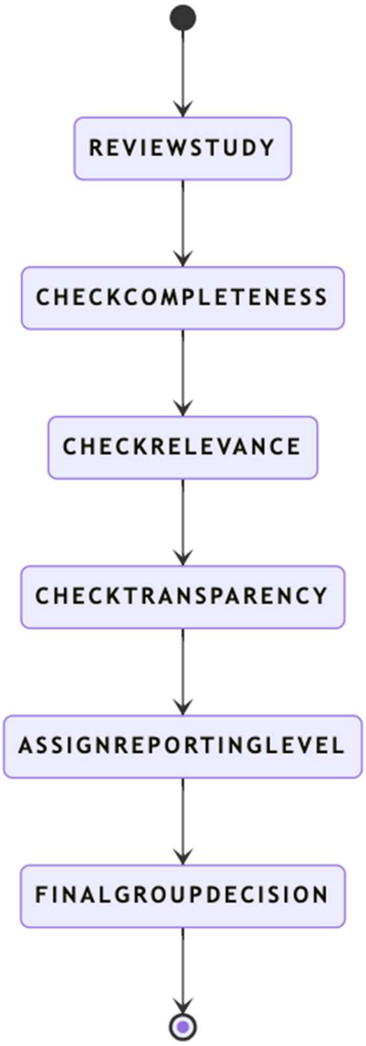

Figure 3. Study risk bias assessment.

2.8. Effect Measures

Obtained results across different studies appeared transparent and homogeneous through the utilization of simple effect measures. The detection performance of IoT systems used percentage data to reflect sensor accuracy and system reliability in reported studies (Thobejane & Thango, 2024). The main outcome included the identified 85% accuracy rate of nitrogen sensors during testing. The effectiveness of different IoT systems or technologies was represented through visual comparison methods such as graphical presentations. The main method used for comparisons evaluated system performance in detecting macronutrients during real-time operations and their response time to water quality changes. Frequency counts were used to identify the frequency of appearance of specific sensors and methods through multiple studies. The basic effect measures enabled the synthesis process to become simpler for comparing studies despite their diverse data types. The method for effect measures used in this study is tabulated in Table 6.

Table 6. Method for effect measures.

Outcome	Measure used	Purpose
Sensor accuracy	Percentage (%)	To show detection performance
Technology comparison	Visual arts, counts	To compare commonly used tools

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System responsiveness	Time recorded	To show how fast sensors respond to water change
Challenges reported	Frequency count	To identify technically recurring issues

2.9. Synthesis

The authors describe their approach for analyzing and processing selected research to achieve conclusions regarding IoT applications within macronutrient surveillance. Study evaluation for synthesis took place first followed by data preparation that culminated in building tables for data visualization and interpretation (Dladla & Thango, 2025). The review used both qualitative methods along with fundamental quantitative approaches to generate significant conclusions from the collected data. Additional information regarding the synthesis procedure is detailed in the following subsections.

2.9.1. Eligibility for Synthesis

Studies advanced for synthesis needed to fulfill three requirements: they needed an IoT specific monitoring system for nutrients while also focusing on agricultural or aquatic settings and offering results about nitrogen and phosphorus and carbon detection. Research authors created a table that compared intervention characteristics across different studies relative to established criteria. The analysis included only studies which met every set inclusion requirement. The research excluded informational models when they lacked empirical evidence. The eligibility for synthesis used in this study is tabulated in Table 7.

Table 7. Eligibility for Synthesis.

Study ID	IoT Application	Environment (Agriculture/Aquatic	Nutrient focus	Outcome Reported	Included for synthesis
1	Smart nutrient Monitoring	Agriculture	Nitrogen, Phosphorus	Improved detection accuracy	Yes
2	Wireless sensor network for water quality	Aquatic	Nitrogen	Real-time monitoring data	Yes
3	Laboratory prototype only	Laboratory only (Excluded)	Phosphorus	No field deployment reported	No

2.9.2. Data Preparation for Synthesis

Multiple preparation steps were applied to research data after its conclusion to make it suitable for comprehensive synthesis. The research team conducted a review to normalize all terminology found between different studies. Standardization efforts included grouping 'Nitrogen sensors' from previously separate names like 'nitrate sensor' and 'NO3 sensor'. Additionally, the classification terms for water environments were brought together under 'aquatic system' by grouping 'pond' with 'lake'. The process required unit consistency as a main concentration point. A conversion factor linked the different units whenever studies presented nutrients using mg/L versus using ppm. Alternatively, the team added narrative descriptions for unit conversion. Treatment was given to studies without reported units by adding footnotes before their information in the data summary table (Pingilili et al., 2025). The study retained its position in synthesis while a note was added when data included incomplete information (such as sensor accuracy not provided). The team was able to mention absent data points but continued with pertinent qualitative findings. The studies remained in the narrative synthesis instead of being eliminated to maintain an inclusive perspective.

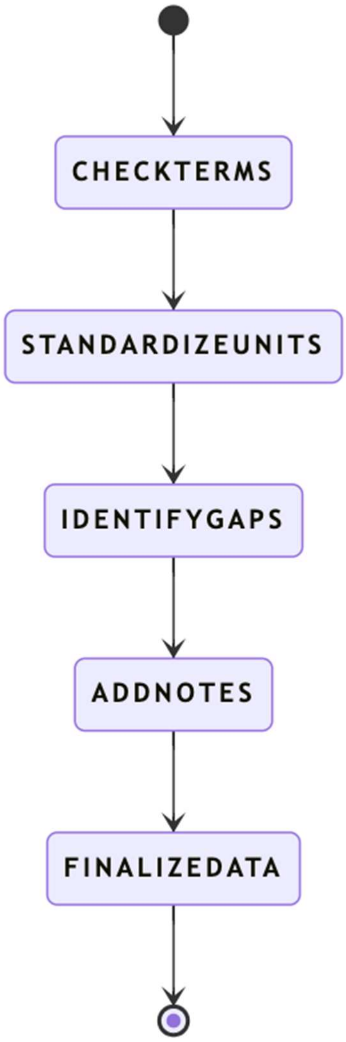

Figure 4. Flowchart for data preparation for synthesis.

2.9.3. Tabulation and Visual Display of Results

A systematic method was applied to both categorize study information before creating visual displays for data representation as shown in Figure 5. The team undertook a systematic review of all information after data preparation where they organized studies following major variables relating to sensor types and environmental conditions and nutrient monitoring types. The applied group-based organization enabled better identification of recurring patterns and suitable comparison of study outcomes. The team implemented visual display formats after performing the groupings. Bar charts together with pie charts helped present distributions plus frequencies which made reading the results simpler for readers. The visual presentation focused on displaying three elements: research equipment utilization along with specific nutrient assessment methods and geographic distribution of research activities (Kgakatsi et al., 2024).

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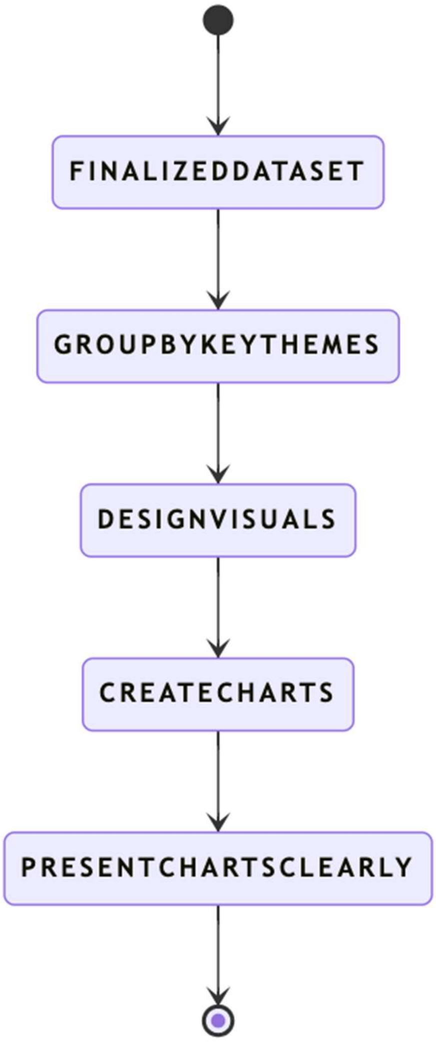

Figure 5. Process for tabulation and visual display of results.

2.9.4. Synthesis of Results

The research group employed both qualitative and descriptive approaches for synthesizing the selected study results as shown in Figure 6. This research approach enabled the team to perform organized analysis and differentiate different findings because the studies employed divergent approaches and reported different outcomes. The qualitative synthesis method enabled researchers to observe recurring positive effects alongside recurrent challenges which appeared across the investigated studies (Chabalala et al., 2024). The descriptive segment involved basic quantification through counting of studies using specified sensors and research approaches toward particular nutrients. The synthesis approach avoided the implementation of meta-analysis software since the research studies displayed inconsistent research design characteristics. The team used spreadsheet applications to group data manually for creating consistent summaries that maintained easy understanding. The authors chose this mixed methodology because they needed to evaluate research amidst their various data collection techniques.

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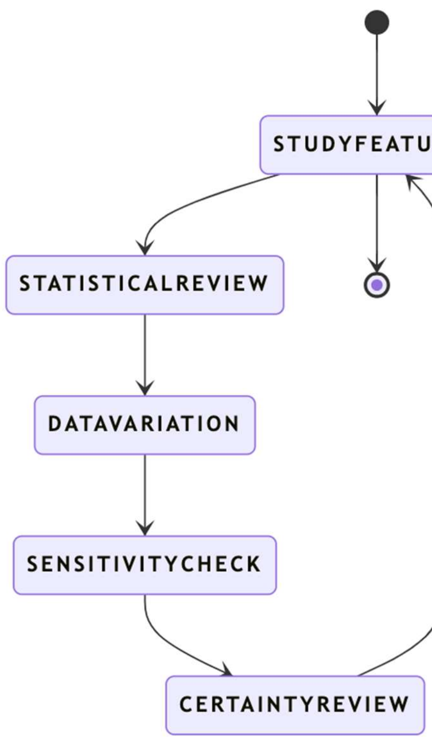

Figure 6. Flowchart for synthesis results.

2.9.5. Exploring Causes of Heterogeneity

The reviewers conducted subgroup analyses to investigate possible reasons behind conflicting study results as shown in Table 8. Researchers organized their investigations into three groups according to field or water-based environmental parameters as well as the monitored nutrient type and choice of sensing equipment including optical or electrochemical systems. The reviewers achieved understanding about outcome influences by analyzing different groups of studies. The combination of optical sensors in aquatic environments produced higher accuracy than basic sensors in soil-based systems. The selected monitoring method helped researchers identify that observed inconsistencies resulted from varied environmental operations and equipment specifications.

Table 8. Table to explore Heterogeneity.

Subgroup Criteria	Findings	Observed differences
Environment Type	Aquatic systems favored sensor accuracy in nutrient detection	Agricultural setups showed more variation due to soil interference
Sensor Type	Optical sensors performed better in clear water environments	Electrochemical sensors had more variability in muddy or low-flow conditions
Nutrient Type	Nitrogen monitoring was most frequently studied	Carbon monitoring was less consistent in method and outcomes

2.9.6. Sensitivity Analyses

Reliability assessments included sensitivity tests that showed how the main research results would compare if studies with incomplete or ambiguous data were eliminated from analysis as shown in Figure 7. Sensor accuracy and nutrient detection outcomes were among the missing key information that the review team identified during their assessment. The dataset lacked the research

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studies before scientists developed a different synthesis method. Research was performed to confirm the robustness of main sensory device in-filtered environmental findings and nitrogen tracing methods with incomplete study reporting. Minor changes occurred in the stable synthesized conclusions because the synthesis studies maintained their results regardless of including or excluding individual research groups (Msane et al., 2024). This strengthened confidence in the overall reliability of the findings.

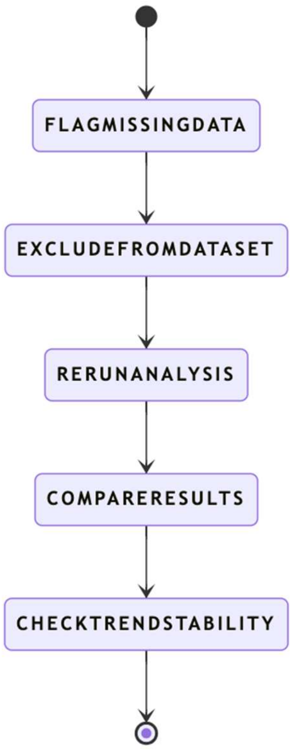

Figure 7. Process for sensitivity analysis.

2.10. Reporting Bias Assessment

In conducting this systematic review of macronutrient monitoring with the use of IoT technologies, all precautions were taken to prevent the risk of bias due to missing results or selective reporting of outcomes. As it was understood that reporting biases have great potential to impact the validity of the review, a rigorous process was followed to assess and minimize such risks. We used both graphic and statistical methods to generate potential biases in the studies that were gathered (Dladla & Thango 2025; Msane et al., 2024). In particular, contour-enhanced funnel plots were used, which provide a visual method to detect asymmetry that would otherwise suggest the presence of publication bias. These plots enabled the discrimination of missing studies due to publication bias from those lost to chance, thereby obtaining a truer representation of the distribution of the underlying data.

In addition to the visual inspection, Egger's test of regression asymmetry was con-ducted where the number of studies allowed, providing an additional level of statistical verification to the assessment of bias. Using both graphical and statistical approaches, we obtained a robust and rigorous evaluation of risk of reporting bias. Significantly, we made no use of any automation tools in this process, relying instead on manual examination and analysis alone. Four individual reviewers carried out the assessment of each plot and regression outcome independently of one another, and differences in their views were ad-dressed through rigorous meetings of consensus (Molete et at., 2025). In areas where disagreement was the most common, a fifth reviewer was called upon to provide an additional viewpoint and to help reach a final decision.

To further improve the strength of the review, manual searches were conducted in different databases, including Scopus, Web of Science and Google Scholar. The manual searches attempted to find any additional studies that were not retrievable using the initial database searches, as a means of addressing the problem of missing studies due to database indexing limitations or selective publication. Cross-referral of various sources helped in minimizing possible gaps in data and strengthened the comprehensiveness of the review process.

As a result of the integrative character of the work on IoT in nutrition monitoring, we realized that traditional means for assessing reporting bias, previously used in clinical fields, would not be fully relevant. Therefore, minor adjustments were made to align the methods of bias evaluation with the technological and health-related context of this re-view. The adjustments assisted in ensuring that both the context and the methodology of the assessment remained valid while being sensitive to the novel aspects of the studies under review.

All methods used in the assessment of reporting bias have been transparently documented in the supplementary materials with this review. This promotes reproducibility and allows future researchers to reproduce or build upon our findings. This commitment to manual, explicit bias assessment, methodological adjustment adaptation, and complete transparency is proof of our commitment to ensuring asperity and reliability to the greatest extent feasible in the synthesis of IoT application evidence for macronutrient monitoring.

2.11. Certainty Assessment

The accuracy of the body of evidence collected in this systematic review on IoT applications for macronutrient monitoring was closely evaluated using a structured quality assessment approach as shown in Table 9. Five carefully selected quality assessment (QA) criteria were used: (QA1) the clear and exact expression of research objectives; (QA2) the specificity and transparency of the IoT system's data capture mode; (QA3) the detailed definition and measurement of macronutrient-related parameters; (QA4) the application of a sound and suitable research methodology; and (QA5) the contribution of study findings toward developing the understanding of IoT's role in nutrition monitoring. All the criteria were scored on a three-point scale: '1' for full compliance, '0.5' for partial compliance, and '0' for non-compliance, resulting in an overall certainty score per study ranging from 0 to 5. Answers to the certainty assessment questions were recorded in a structured format, and each study's overall score was scaled to a percentage to facilitate comparative scoring (Khanyi et al., 2024). Studies with a full score were graded as 100%, reflecting good methodological quality and high relevance to review purposes. Mid-level scores reflected moderate to low levels of certainty, reflecting a balanced judgment of the strength of evidence for included literature in the review.

Table 9. Certainty Assessment Results for Collected Literature on IoT in Macronutrient Monitoring.

Ref.	QA1	QA2	QA3	QA4	QA5	Total	% grading
Paerl et al., 2016, Bai et al., 2025, Strokal et al., 2015, Wurtsbaugh et al., 2019	1	1	1	1	1	5	100
Martínez et al., 2020	1	1	0.5	1	0.5	4	80
Park et al., 2020	1	0.5	0.5	1	0.5	3.5	70
Mielcarek et al., 2023	0.5	0	0.5	0.5	0	1.5	30

To enhance the reliability of the certainty, estimate even further, the GRADE process was embraced and adapted to accommodate the specific situations of this review. The GRADE process presented a system-based approach of grading the quality of the evidence through the primary outcomes based on the consideration of numerous important factors. Initially, the certainty in the effect estimate reported was explored by looking at the sample size and reported confidence interval width within the trials included. Large sample size and narrow intervals were categorized as having high certainty evidence, whereas wider intervals represented greater uncertainty (Thango & Obokoh, 2024). Secondly, consistency between studies was determined through comparison of results and investigation of heterogeneity of findings. Very consistent results in both settings and populations increased confidence in the evidence, and differences were explored in detail for potential methodological or contextual reasons. Third, directness of the evidence was determined by observing how closely the populations, interventions, and outcomes resembled the particular questions being investigated in this review. Direct evidence was graded more positively, indirect outcomes being graded lower as a consequence.

Additionally, the risk of bias of the study was determined separately for every study using the modified Cochrane Risk of Bias tool. The low risk of bias studies increased the certainty, while because of methodological limitations or selective reporting, the studies were conservatively downgraded. Lastly, suspicion of publication bias and influence because of missing studies were added to the grade of certainty to provide for missing data with implications on conclusions (Ngcobo et al., 2024). Using these diverse aspects, certainty of evidence was graded in four grades: High, Moderate, Low, or Very Low. High certainty was used where the evidence base was robust on all the factors examined. Moderate certainty was used for minor worries regarding one factor, for instance, small heterogeneity or moderate risk of bias. Low certain-ty was reserved for several significant concerns across more than one domain, and very low certainty was reserved for outcomes where serious concerns compromised confidence across all assessed domains.

All the certainty ratings were done independently by reviewers for them to be valid and unbiased, and discrepancies were addressed through consensus meetings. Through such systematic and transparent process, the review gives a rich and quality synthesis of the available evidence regarding the use of IoT technologies to monitor macronutrient in-takes and concentrations.

3. Results

3.1. Study Selection

The flow chart in Figure 8 demonstrates the procedure of study selection included in this systematic review on macronutrients of key significance. Technical literature on Nitrogen (N), Phosphorus (P), and Carbon (C) was explored across various academic databases using the keywords given in the "Search Strategy" section. Articles were screened against the inclusion and exclusion criteria mentioned in the "Eligibility Criteria" section. The original search of all the databases selected produced some 20 251 research studies, which were initially screened for titles and abstracts. As described in Figure 9, a total of 82 studies were ultimately found to be relevant to the review's focus on macronutrient dynamics: 59.52% were from Google Scholar, 16.67% from Scopus and 23.81% from Web of Science. Among the initial 149 shortlisted records, the material composition was of book chapters for 4.76% and journal articles for 95.24% - see Figure 9. After the disposal of duplicate entries, there were 82 unique studies procured and assessed using full-text analysis. All 82 studies met the specified eligibility criteria and thus made it into the final review. There was no exclusion of studies during the full-text screening to include comprehensive representation of literature of Nitrogen, Phosphorus, and Carbon in freshwater and terrestrial ecosystems.

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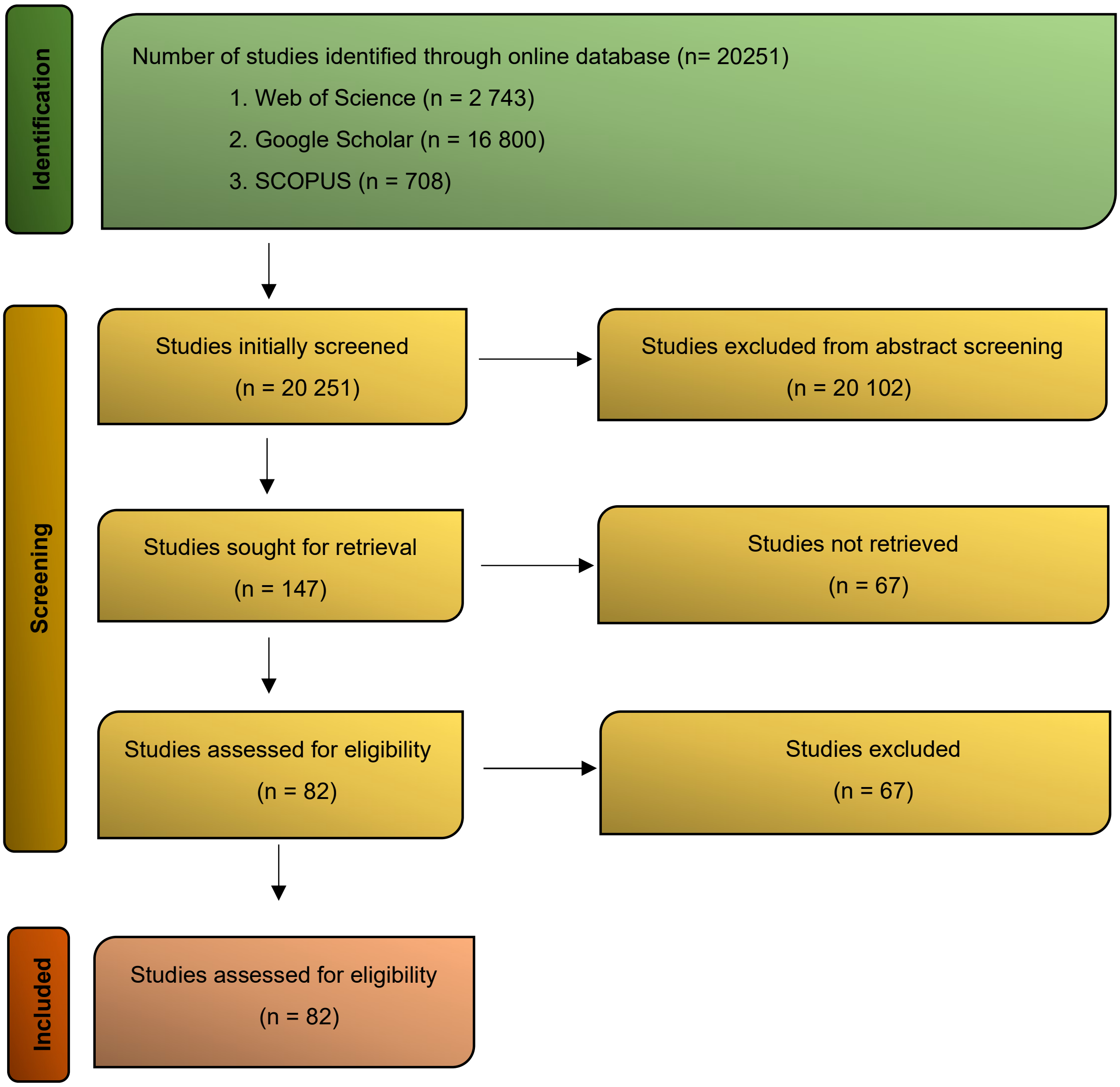

Figure 8. Proposed PRISMA Flowchart.

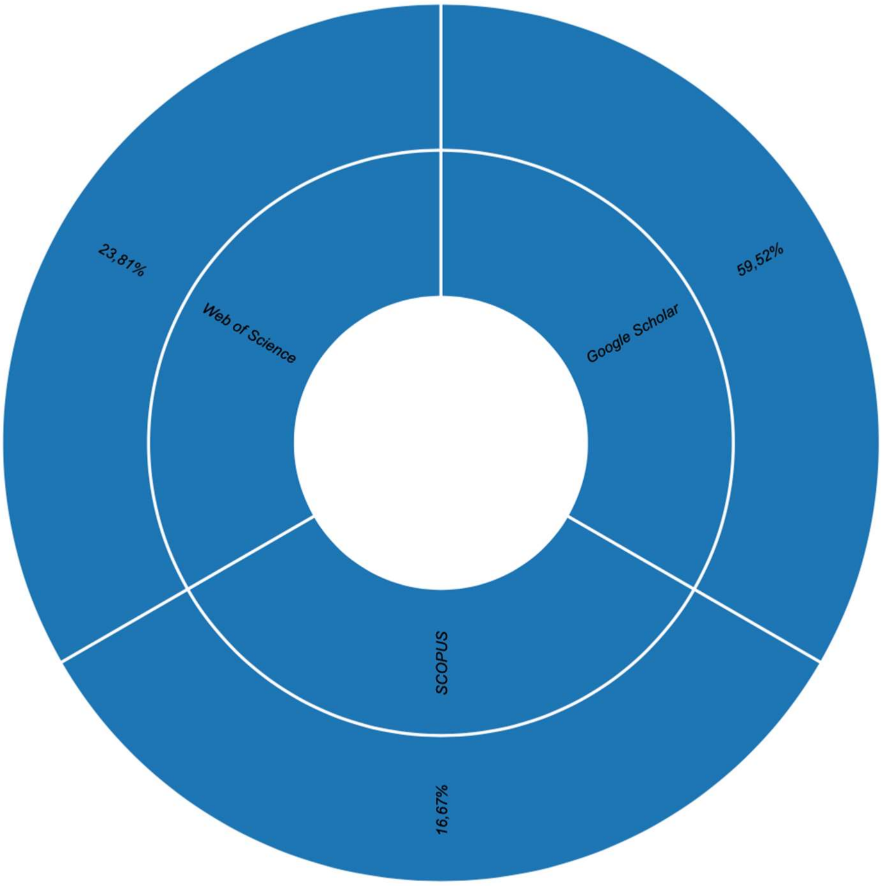

Figure 9. Distribution of Online Database.

3.2. Study Characteristics

82 context-specific papers published between 2015 and 2025 mentioned all aspects of management for the most significant macronutrients causing eutrophication and algal bloom. Publication trend, as in the bar graph shown below – Figure 10, demonstrates irregular but generally continued interest in nutrient process, pollution mitigation, and control of practices in the whole of the last decade. The most productive year was 2017, with 15 publications, and a massive increase in interest. 2023 recorded 12 and 2021 recorded 10. Mid-range publications were recorded in 2015 (7), 2016 (6), 2019 (7), and 2020 (9), and there was lower interest in 2018 (3) and slightly lower again in 2024 (5) and 2025 (4). These trends reflect that while the interest has been consistent, certain years had peaks most likely due to the growing environmental concerns or research grant projects.

Distribution of source types – Figure 11- is comprised of 4.76% book chapters and 95.24% journal articles, with journal articles being the common format for presenting findings. These also contribute significantly, with book chapters contributing in smaller proportions. Despite this growing literature, there still exists a gap in systematic review. Bridging this gap has the potential to synthesize piecemeal evidence, conduct an integrated assessment of measures for nutrient regulation, and inform evidence-based policies for controlling eutrophication and rehabilitating aquatic ecosystems.

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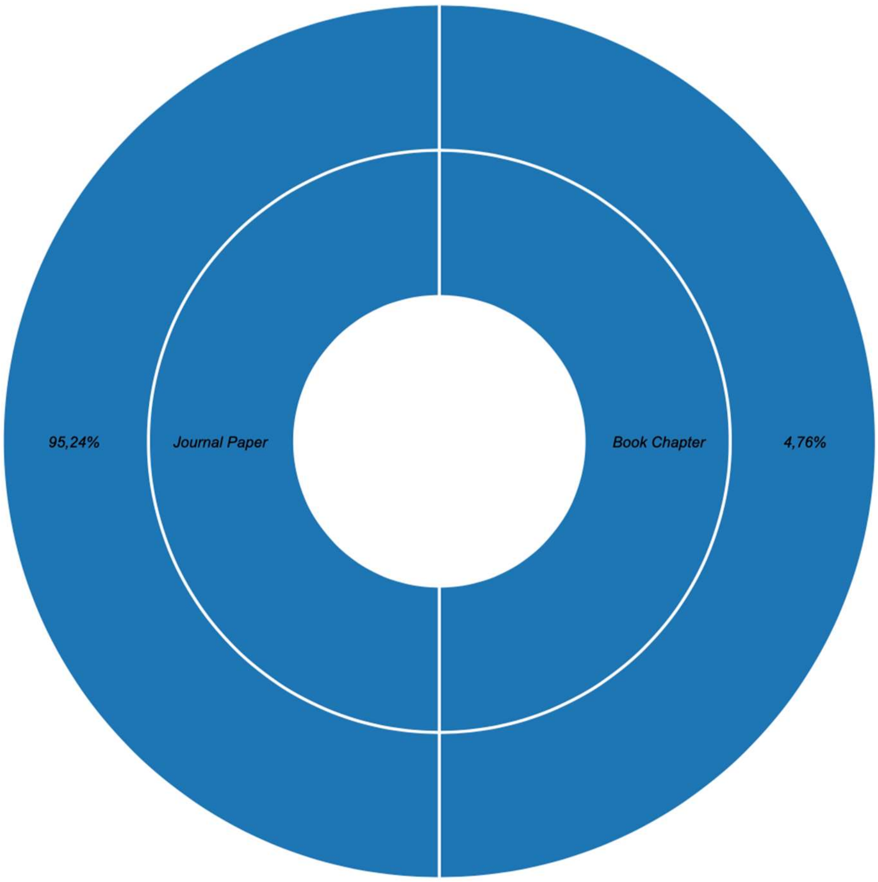
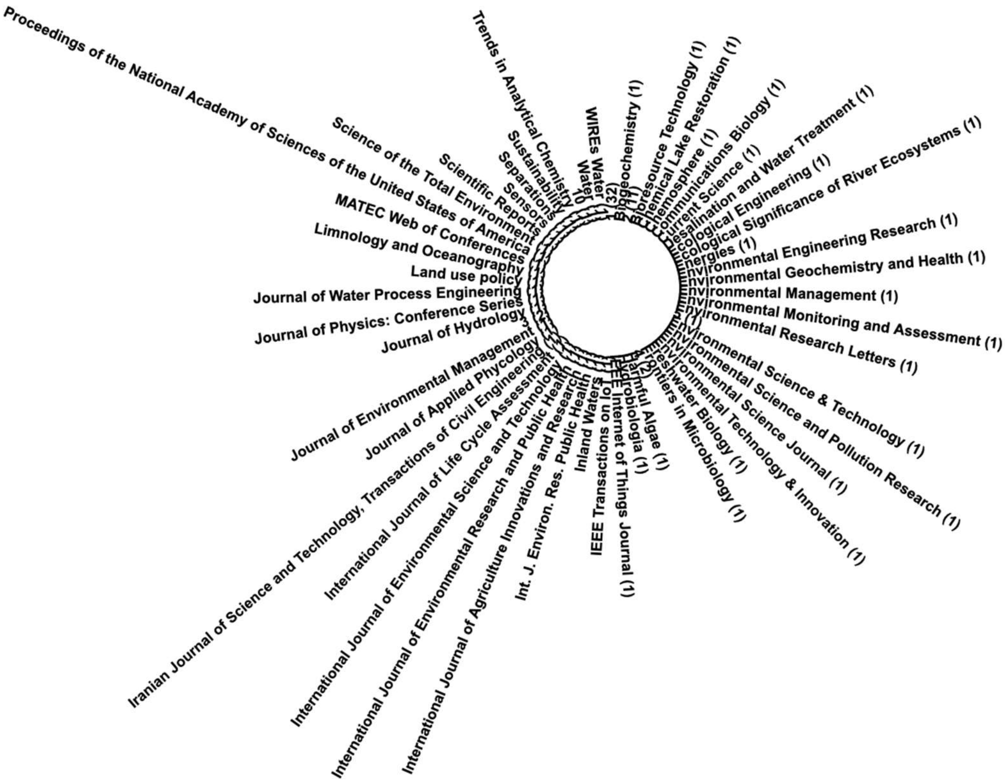
Figure 10. Annual Research Publications.



(**a**)



(b)

Figure 11. Identification of the Type of Research.

Table 10. A summary of the research's development over time, based on the publication dates of each study.

Year of Publications	Journal Article	Book Chapter
2015	7	0
2016	6	0
2017	15	0
2018	2	0
2019	7	0
2020	9	0
2021	8	2
2022	4	2
2023	11	0
2024	5	0
2025	4	0

The bar graph in Figure 12 demonstrates geographic distribution of studies on nitrogen, phosphorus, and carbon management as part of eutrophication and harmful algal blooms. The lead is being taken by China with 26 papers, thereby justifying serious national investment in studies of nutrient pollution and ecosystem remediation. The United States is second with 15 papers, indicating strong institution led research into nutrient mitigation. Spain (7), Canada (5), and India (4) are examples of active use of nutrient regulation in different water systems.

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Developed nations with average contributions - 2 each include the United Kingdom, Austria, Germany, Greece, Korea, Malaysia, and the Netherlands, which are examples of sustained research interest in both developing and developed continents. A broader set of nations, including Brazil, Finland, Czech Republic, Hong Kong, Iran, New Zealand, Poland, Taiwan, Turkey, Uganda, and an assortment representing Oman/China/Australia/Malaysia, provided 1 publication each. Such variation in authorship is indicative of increasing global interest in nutrients as a source of ecological issues and underscores the importance of global, cross-national collaboration to address aquatic ecosystem health.

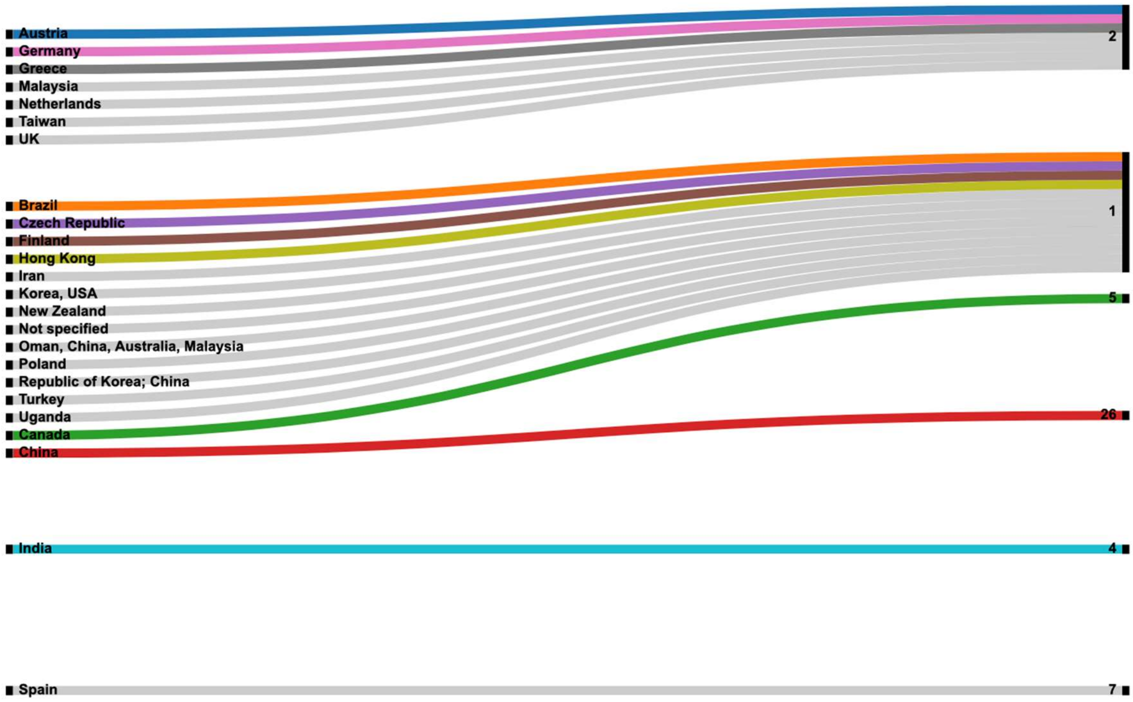

Figure 12. Distribution of Research Papers Worldwide.

The topical distribution reflects a clear emphasis on practical nutrient-management concerns in the bar graph in Figure 13, over half of the papers - 52.38 % report on Nutrient Pollution & Removal, in keeping with the need for developing and optimizing technologies and methods for removing excess nitrogen, phosphorus, and carbon from water systems. The second most salient category, Algal Booms & Eutrophication with 25.00 % of papers, testifies to worldwide concern for ecosystem disruption and macronutrient-driven toxic algal events. A slightly less substantial but still significant amount of effort - 11.90 % is directed toward Water Quality Monitoring & Modeling, with a focus on the efforts to monitor nutrient dynamics in real-time and model their implications using computational tools. Ecological & Biogeochemical Processes research - 9.52 % supplies fundamental knowledge of natural transformation and cycling of nutrients within aquatic ecosystems, with the lowest-researched Wastewater Treatment & Nutrient Management at 1.19 % perhaps reflecting an apparent research gap in applied treatment technology within engineered systems. This suggests a primary research environment dominated by attempts at understanding and alleviating nutrient-caused ecological disruption, with considerably less research in treatment plants and process-level biogeochemistry.

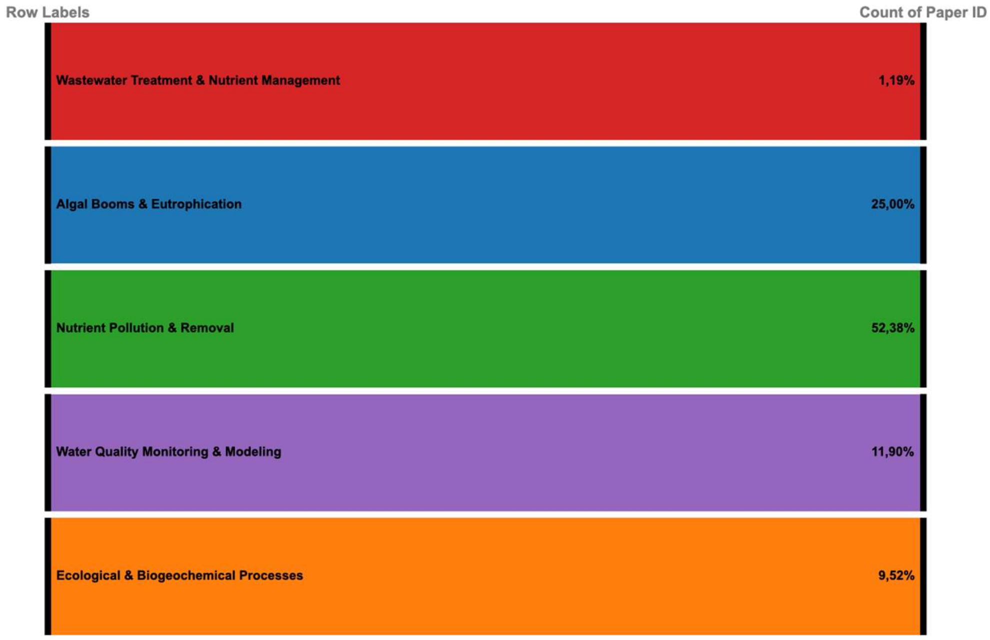

Figure 13. Investigated Water Aspect.

The studies reporting nitrogen showed in Figure 14 shows that researchers most commonly record overall nutrient concentrations, fully 55.95 % of the nitrogen-related observations –general nutrients concentration were of this category. Far less common are detailed speciation or removal rates: total nitrogen and its primary forms (TN, NH_4^+–N, NO_3^-–N, NK_3–N) each accounted for 7.14 % of observations, as did percent nutrient reduction and removal efficiencies and nutrient loading rates (expressed in kg/ha, g/m², or t/km²/yr). The remaining 22.62 % is of the other metrics and variations. Practically speaking, it means that more than half of nitrogen research in the literature is restricted to snapshots of bulk concentration, whereas more in-depth investigation of nitrogen species, treatment efficiency, or loading dynamics are relatively rare. This imbalance offers opportunities for additional research to advance our understanding of nitrogen cycling through more emphatic focus on both speciation and efficiency-based measures linking concentration data to treatment outcomes or watershed-scale loadings.

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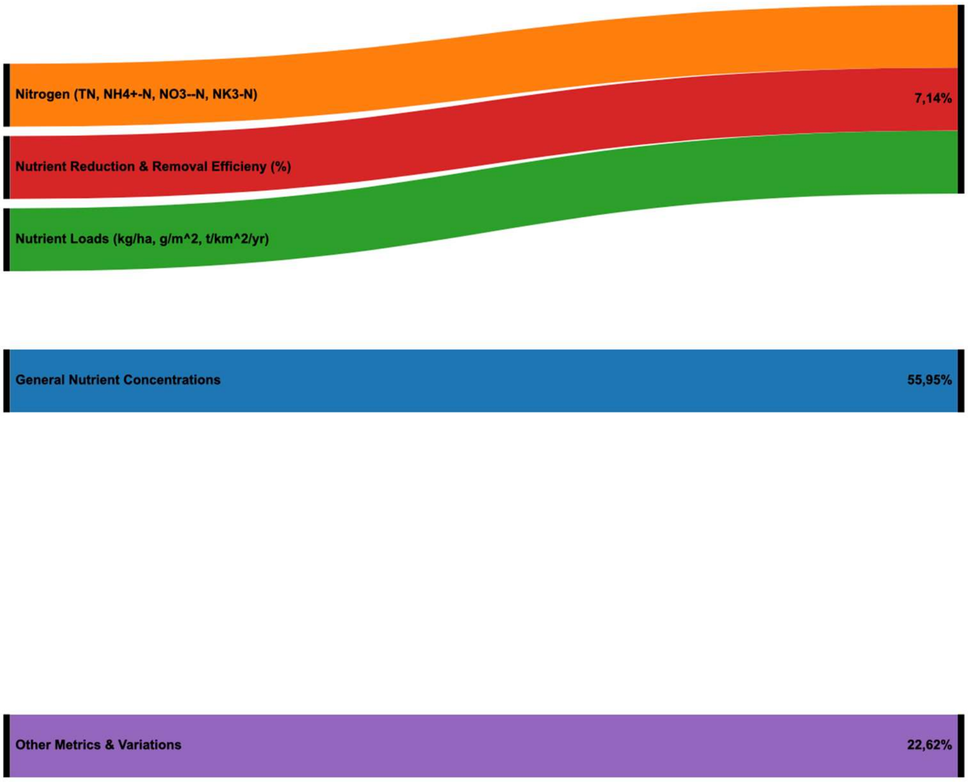

Figure 14. Distribution of Nitrogen Assessment Metrics in Monitoring Studies.

The quantification of phosphorus presented in Figure 15 shows that overall nutrient levels were addressed by over half of the studies (54.76 %), and therefore the most frequent category reported. Individual speciation of phosphorus (total phosphorus, PO_4^{3-}, dissolved inorganic phosphorus, and non-dissolved inorganic phosphorus) was found in 9.52 % of the studies, indicating a reduced but real focus on specifying different forms of phosphorus. A nutrient reduction & removal efficiency of nutrients is an 8.33 % stake of the study that aims to quantify by how much various treatment or mitigation measures decrease phosphorus amounts. Quantifying the nutrient loads (in tons, kg/ha, g/m², or t/km²/yr) occupies 4.76 %, an expression of all the more interest in quantifying the phosphorus fluxes on larger spatial extents. The "Other Metrics & Variations" category, less common or more specialized approaches to defining phosphorus dynamics accounts for 22.62 % of results, suggesting a substantial minority of research establishing new or context-specific phosphorus metrics. These percentages mark a research landscape with a prevalence of general concentration measurements, more specialized speciation, efficiency measurement, load measurement, and novel metrics finding complementary niches.

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Figure 15. Proportional Distribution of Phosphorus Measurement Categories.

Of the carbon centred work included as illustrated in Figure 16, the vast majority (79.76 %) fell into an umbrella "Other Metrics & Variations" category, implying that the most researchers are studying wide-ranging carbon-related parameters other than standard measures. The second largest segment with 13.10 % gave only total concentration values, meaning that straightforward quantification of total carbon is common but no longer the greatest in number. Individual studies targeting carbon & organic matter were comparatively small in number with 3.57 %, while those measuring pollutant removal & reduction efficiency in the form of carbon were only 2.38 % of the sample. An infinitesimal percentage, a mere 1.19 %, logged a baseline or reference measurement - indicated here as 0.123, which indicates that very few publications have this kind of fixed point measurement. These results suggest that while basic concentration measurement remains the norm, there is considerable heterogeneity in the measurement of carbon and fairly little focus on standard organic matter metrics. Forthcoming research can hence benefit from more uniform reporting of carbon concentrations and efficiencies to support better study comparability.

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Figure 16. Distribution of Carbon Metrics.

The distribution of sensor technologies, more broadly, analytical techniques are used to quantify macronutrients in aquatic ecosystems is largely to "Other Analytical Methods," which account for over half of all techniques (n=52). Traditional laboratory-based techniques like spectrophotometry and optical analyses are the second largest group (n=9), followed by electrochemical and ion-selective sensors (n=7) and multi parameter water quality sondes that combine (n=6). Software & computational model equipment occurs comparatively less (n=4), a reflection of their comparatively newer use. Only highly specialized or single-application technologies such as the LI-COR LI-1400 PAR sensor combined with a YSI Pro-ODO probe and FluoroProbe, MODIS satellite sensors, and nitrate and nitrite analyzers combined with ion chromatography each comprised 1 application as demonstrated in Figure 17. While field-deployable sensor platforms are very fashionable, the majority of studies are still founded on conventional laboratory analyses, and more recent remote-sensing or in-silico approaches are still quite rare.

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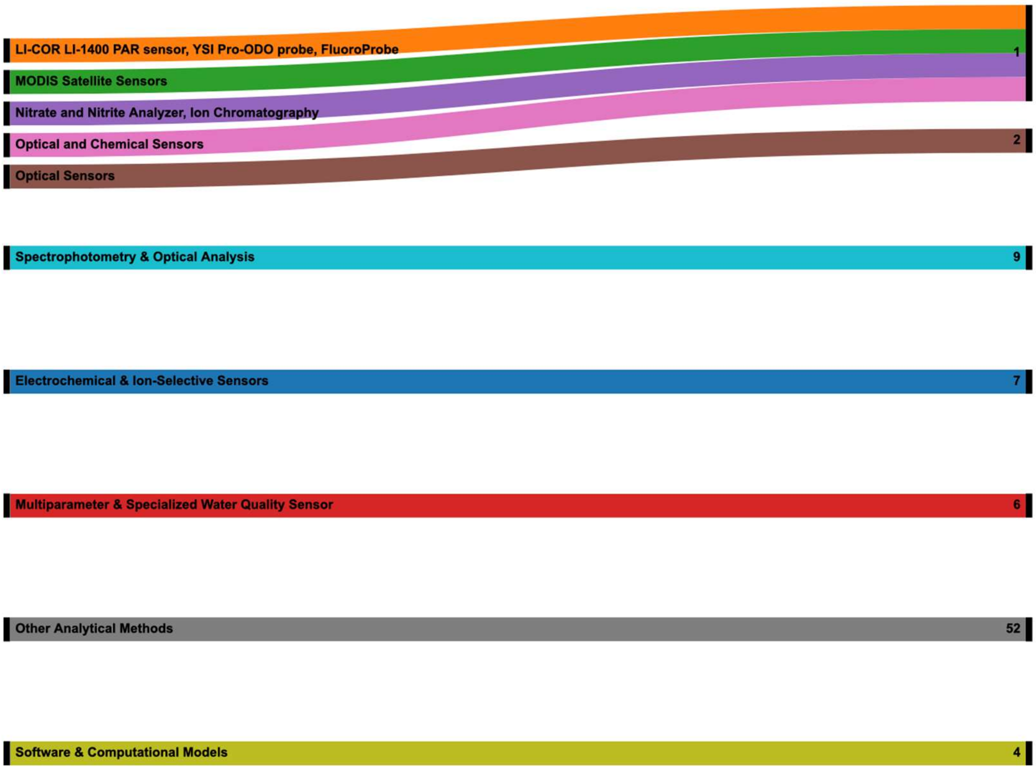

Figure 16. Sensor and Analytical Method Frequencies.

Figure 17 demonstrates the distribution of reported microcontrollers used in macronutrient monitoring studies is heavily weighted toward unreported hardware, 75% of studies simply didn't say what controller they used. Of those studies that did say what platform they used, Arduino variants are by far the most common, at a total of 10.71%. ESP8266 boards are next at 4.76%, with the newer ESP32 at 3.57%. All the other controllers such as Teensy 3.6, Wemos D1 Mini, Mike Basin, Load Calculator, ESPE2, and Time-Lag Analysis with PCA, each occur at only approximately 1.19%. Arduino-compatible platforms are common among authors who do report hardware, by far the most studies do not report them at all, shortening the reproducibility and comparability of IoT implementations across the domain.

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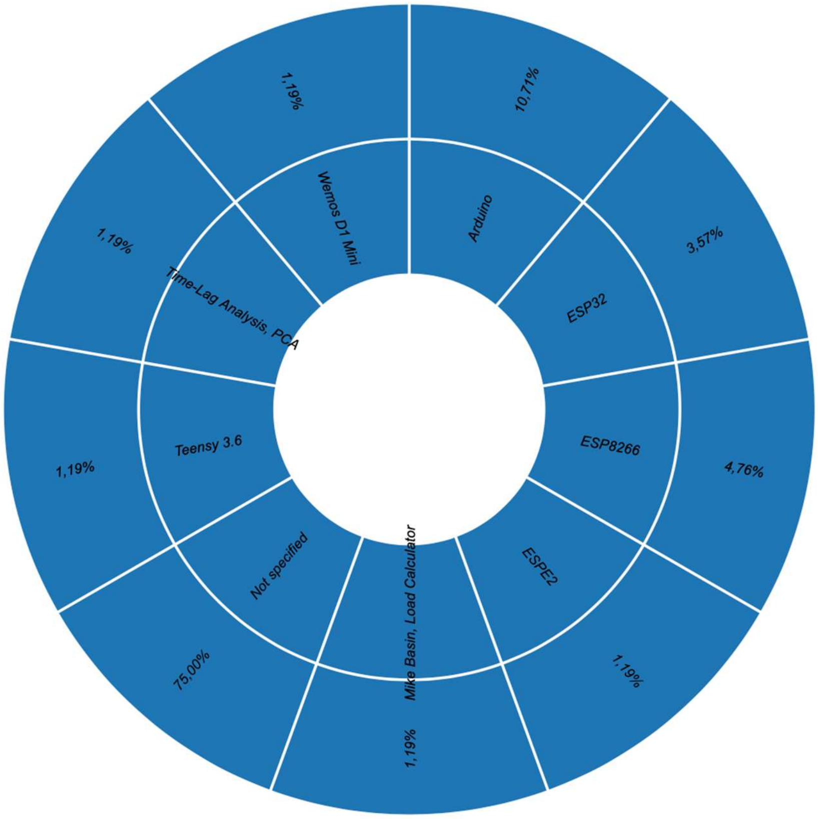

Figure 17. Distribution of Microcontroller Platforms.

Distribution of connectivity types across macronutrient monitoring studies as illustrated in Figure 18, reflects a stunning lack of reporting, for 70.24 % of the articles, the communication medium was not specified. Of those articles that explained a connectivity solution, Wi-Fi and Wireless implementations are both 10.71 % of the cases, thereby being the most popular technologies. LoRa appears in 2.38 % of the studies, Arduino-based GSM/GPRS, IoT-based, remote sensing, wired, and Zigbee used only 1.19 % of the literature each. Although certain niche protocols (LoRa, Zigbee) and traditional wired approaches are explored, the field typically favors popular wireless infrastructures, if they're mentioned at all and that authors prefer to omit crucial methodological detail about their data-transmission equipment from their reports.

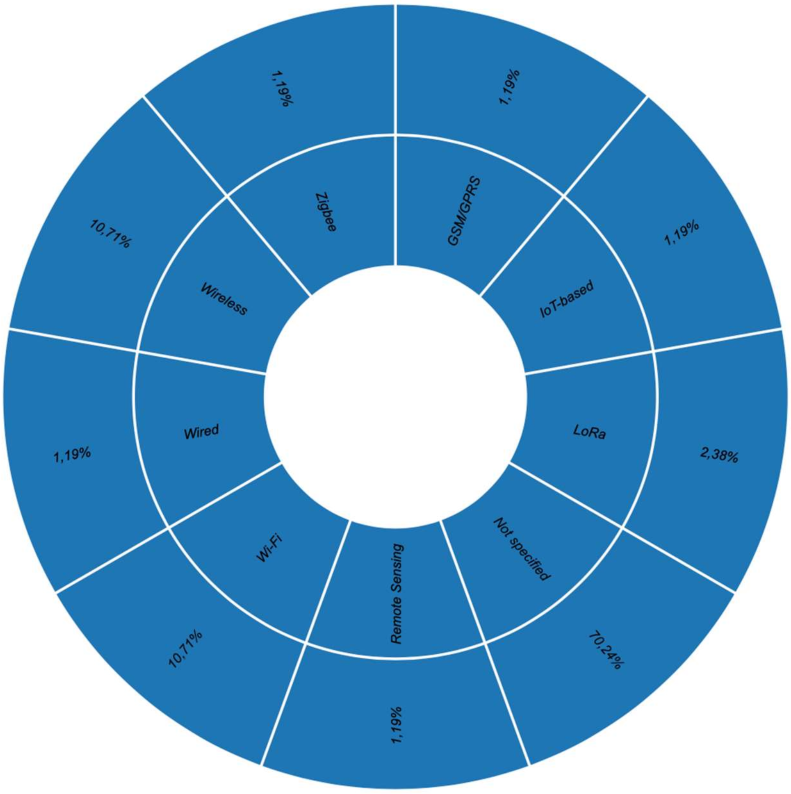

Figure 18. Distribution of Connection Types.

The studies that described the cloud environments as illustrated in Figure 19, 16.67% leveraged dedicated Cloud Service Providers, which reflects a definite but limited preference for scalable, managed back-end services. An even smaller sub-group (5.95%) utilized specialized Cloud IoT platforms and middleware, products specifically designed to manage device connectivity, stream processing, and edge-to-cloud integration. A mere 2.38% used more general cloud computing or infrastructure services that did not contain IoT-specific capabilities, so most researchers do recognize the value in purpose-built IoT middleware. A complete three-quarters (75.00%) of papers said nothing of the cloud environment at all, which could be a marker of a documentation discrepancy or a belief that cloud specifics were of no use in model or sensor performance. The extremely high "unspecified" rate highlights an important reporting bias, future research would be improved by reporting cloud architectures explicitly to improve reproducibility and allow more advanced comparisons between studies.

Figure 19. Distribution of Cloud Used.

The software-use information illustrated in Figure 20 shows that a large majority of studies (36 out of 84) did not report the tools they used, reflecting reporting deficiency or heterogeneity of custom codes that authors did not deem necessary to describe in great detail. Of those that did, "Programming Languages & Statistical Software" constitute the second largest group with 24 studies, reflecting the field's dependency on general purpose analysis environments. Closest behind, 5 studies each purportedly utilized “MATLAB, R” specifically, highlighting those packages application towards algorithm development and data analysis in the environmental observation. 9 more papers classified their software as being more generally "Statistical & Data Analysis Software", and 5 utilized GIS & hydrological modeling programs, attributing the role of spatial analysis to nutrient-loading assessments. More specific forms - AI/ML optimization tools, engineering & experimental-design toolkits, and IoT & software development, were rare (1, 2, and 2 studies respectively), which reveals that although these approaches are now beginning to emerge, they remain specialty compared with mainstream statistical and general programming tools.

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Figure 20. Distribution of Software Used.

3.3. Risk of Bias in Studies

Figure 21 illustrates the quality of research studies that target macronutrient management, based on the Newcastle-Ottawa Scale. The studies were categorized into three levels: Low (1–2 stars), Moderate (3–5 stars), and High (6–7 stars). Only a handful 5 were in Low Quality, possibly due to small experimental scales, absence of nutrient monitoring protocols, or methodological weaknesses in identifying nutrient pathways and ecosystem responses. The largest number of publications - 37 in all, were rated Moderate Quality, which meant that while these papers contributed useful information on nutrient dynamics, they may have lacked complete nutrient loading analyses, truncated temporal data, or incomplete ecosystem recovery analyses. In any case, they form a critical mid-level literature that communicates the complexity of nutrient interactions despite some deficiencies in design.

The most powerful group consisted of 40 High Quality studies, which meant strict experimentation, clear quantification of nutrients, and comprehensive ecological assessments. These analyses most likely included long-term monitoring, multi-nutrient evaluations, and system-level quantifications, the best possible foundation for evidence-based strategies for reducing nutrient loading and restoring aquatic balance. Overall, this assessment of study quality gives assurance that current scientific evidence for nutrient management intervention is reliable and locates places where better methodological balance will increase the cumulative knowledge and ecological impact of the discipline.

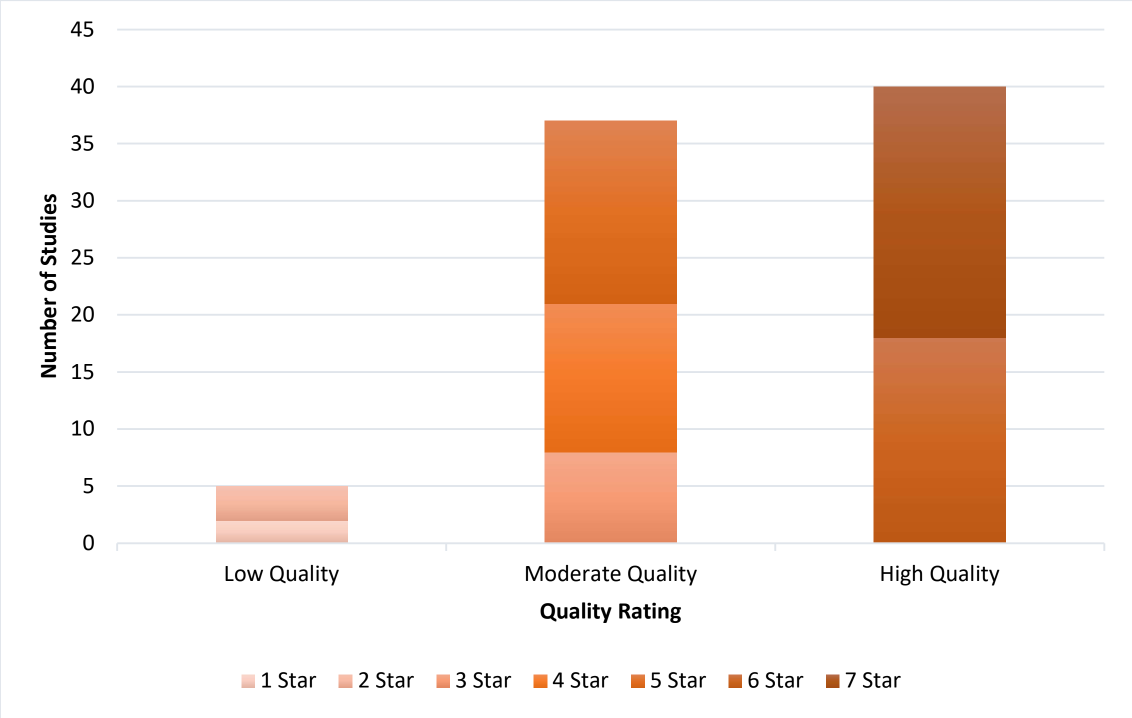

Figure 21. Using the Newcastle-Ottawa Scale to Assess Study Quality.

3.4. Results of Individual Studies

Figure 22 is an overview of model performance metrics and methodological approaches utilized in empirical analyses of macronutrient regulation in aquatic ecosystems. The most common form is Statistical Analysis & Modelling and has been employed in 36 studies. It reveals widespread use of conventional statistical routines to determine nutrient processes and recognize intervention effect. Not Specified methods were applied in 28 studies, a high level of lack of transparency or specificity in reporting model evaluation plan, which can affect reproducibility and comparison between studies. Regression & Advanced Modelling Techniques were applied in 10 cases, showing growing interest in more advanced predictive models capable of handling non-linear nutrient interactions or scenario-based simulation.

Experimental & Computational Modes were employed in 7 studies, which were typically laboratory experiments involving nutrient cycling or computational fluid dynamics models to simulate nutrient transport. Less frequent but helpful studies that have employed individual tools are Accuracy, Reliability, Tolerance with 3 studies. MAE (Mean Absolute Error), Precision, MATLAB, Python tools with 2 studies. This review demonstrates the overwhelming emphasis on statistical modelling, a wide deficit in reporting quality, and little but emerging utilization of advanced and computational techniques in nutrient assessment methodology.

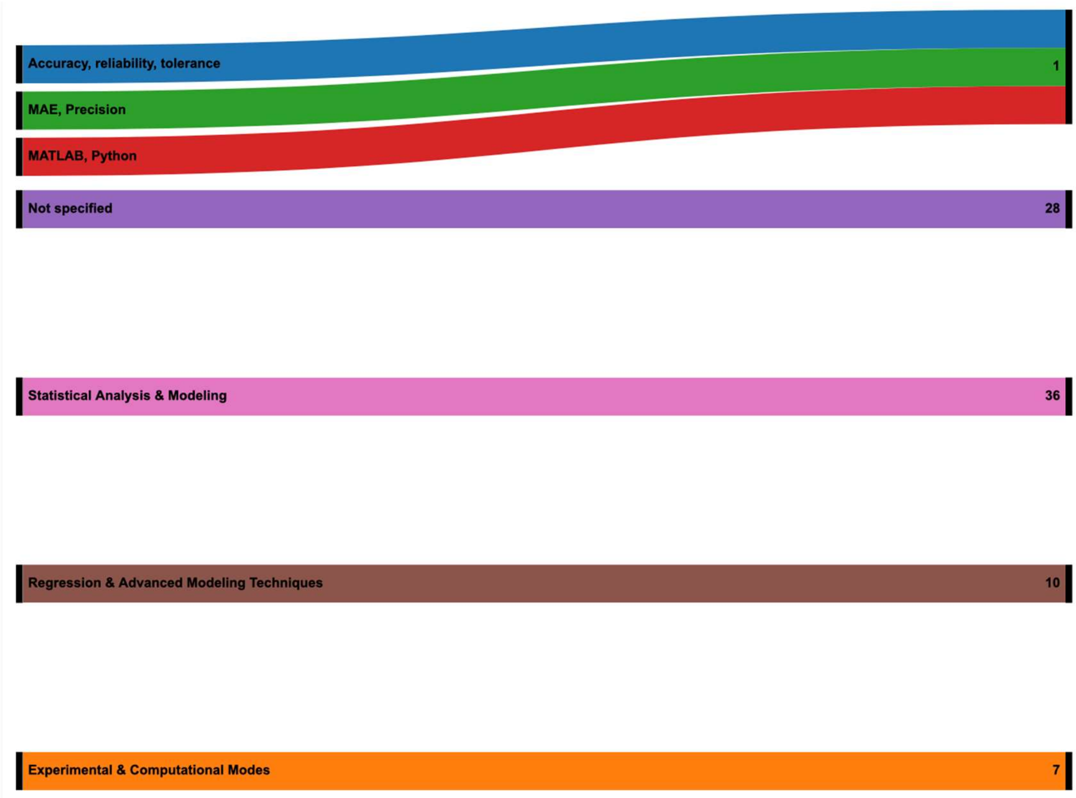

Figure 22. Best Practices for Effective Macronutrient Management in Aquatic Ecosystems.

3.5. Results of Synthesis

3.5.1. Examining Study Characteristics and Potential Biases

This systematic review synthesis comprises 82 relevant studies reporting the cycling dynamics of the macronutrients Nitrogen (N), Phosphorus (P), and Carbon (C) in aquatic ecosystems and their effects on algal blooms and eutrophication. The literature represents a ten-year period of research (2015–2025) and demonstrates worldwide academic interest by developing and developed nations. Methodologically, the study takes a three-fold de-sign structure: quantitative surveys - dealing with nutrient dynamics and pollution control policies, qualitative case studies - providing contextual insight into regional problems, and experimental protocols - investigating causality in nutrient mitigation, with mixed-methods approaches bridging these paradigms. The evidence was purposively extracted from Scopus, Web of Science, and Google Scholar, high-impact sources of plural disciplinary perspectives.

The Newcastle-Ottawa Scale was used to ascertain the quality of the studies, which were classified as High (6–7 stars), Moderate (3–5 stars), and Low (1–2 stars) quality scores. Almost a minority of the trials (48.8%) reached a High-quality criterion (40) with intensive monitoring, measurement of nutrient concentration, and analytical intensity. Moderately quality-scored trials (45.1%) were less methodologically open, especially in the reporting of data and methodology. Impaired-quality trials (6.1%) were in higher risk of selective reporting, emphasizing the demand for cautious interpretation where methodologic transparency is weakened. On the average, proof is at low-to-moderate risk of bias, affirming validity of synthesis but hinting at especial weakness in overseeing protocols for nutrients and evaluation of the ecosystem towards longer timescales.

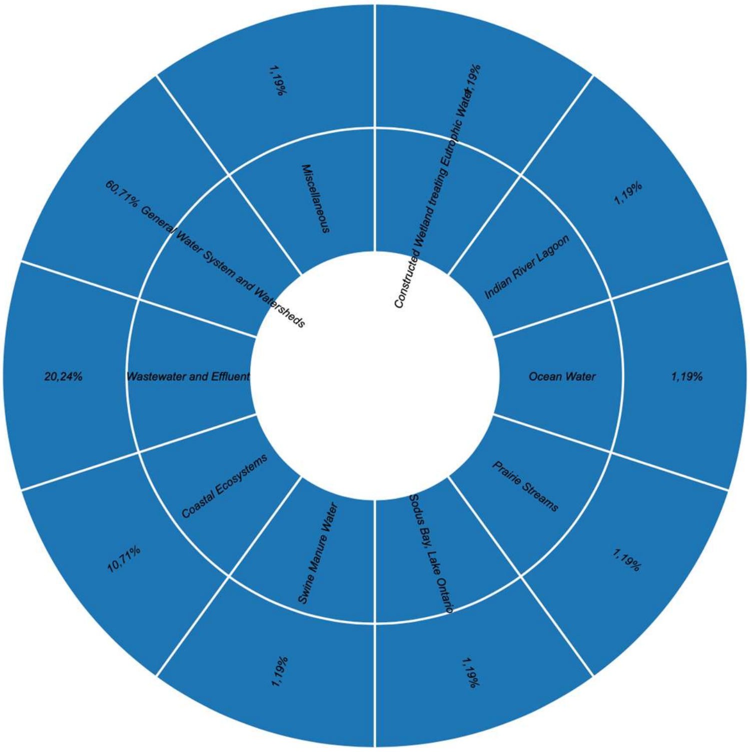

Figure 26. Distribution of Water Sources and Quality Assessment Across Studies.

3.5.2. Statistical Syntheses

A qualitative review of the 82 included studies revealed variability in research area, methodology, and study quality regarding macronutrient control, i.e., Nitrogen (N), Phosphorus (P), and Carbon (C). Quantitative approaches dominated, with 36 studies (43.90%) employing statistical analysis and modeling techniques. This is a very strong indication of evidence-based evaluation of nutrient process and intervention effect within the field. Computational and experimental methods were encountered in 7 studies, and novel regression techniques in 10, reflecting growing need for predictive and simulation models. 28 studies also failed to indicate methodology clearly, reflecting a massive transparency gap affecting reproducibility and comparison across studies.

Thematically, the majority of studies (52.38%) focused on Nutrient Pollution & Removal, followed by Algal Blooms & Eutrophication (25.00%). Less was investigated for Water Quality Monitoring & Modelling (11.90%), Biogeochemical Processes (9.52%), and Wastewater Treatment & Nutrient Management (1.19%), as seen in Figure 14. The varied themes reflect disparate sectoral interests, anything from agricultural runoff to municipal wastewater and lake ecosystem restoration.

With regard to the quality of the studies, as rated per the Newcastle Ottawa Scale, 48.78% (40 studies) were of high quality, 45.12% (37 studies) of moderate quality, and 6.10% (5 studies) of low quality. This distribution suggests a generally robust evidence base to inform nutrient management interventions. It also points to the need for increased methodological rigor and reporting transparency, especially in studies conducted in lower-resourced settings or interdisciplinary areas.

3.5.3. Exploring Variations in Data

The review finds significant differences among developed and developing countries regarding the management of primary macronutrients like nitrogen, phosphorus, and carbon. Among the 82 reviewed studies, it is evident that developing countries generally have entrenched issues like limited

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budget, weak monitoring systems, and brief technical experience. These barriers tend to derail efforts aimed at consistent and effective nutrient control, particularly in freshwater and terrestrial environments where institutional backing is either fragile or patchy.

By comparison, developed economies tend to exhibit far more structured and resilient strategies for managing nutrient loads. By comprehensive environmental surveillance, advanced modeling tactics, and institutionalized pollution policy, countries like China and America, world leaders in research productivity, have prompted investment in nutrient surveillance, treatment technology, and intergovernmental cooperation. Through such a comparison, the ways in which institutional and economic contexts determine the depth and breadth of nutrient governance can be seen to be significant. While long-term, well-planned nutrient control programs are routine in developed nations, developing nations are too frequently plagued by disruption caused by financial constraints or administrative inefficiencies.

These results hold important implications for both theory and practice. They strengthen, first, the systems ecology approach in illustrating how social, economic, and environmental elements inexorably mold the destiny of nutrient management initiatives.. Second, the research indicates the value of the manner in which various countries need varying approaches. To poorer nations, it might be a powerful factor to invest in infra-structure, to train people, and to track changes in the environment in real time. For wealthier countries, maybe more would be invested in building and developing from the base already made. Overall, this research permits us to discover more about the role of economic factors in the way that countries address nutrient pollution and problems like eutrophication.

3.5.4. Sensitivity Analyses Results

To assess the robustness of conclusions and examine the impacts of data source changes, study quality changes, thematic focus, and methodological quality on overall conclusions, sensitivity analyses were conducted across various systematic review levels. Analysis of data sources showed Google Scholar (59.52%) generated the majority of the studies, followed by Web of Science (23.81%) and Scopus (16.67%) in declining secondary importance. Despite differences in the range of indexing, research findings in all three databases were consistent in emphasizing the dominance of eutrophication and nutrient pollution topics. There was no significant difference in thematic emphasis or quality of research across the databases, which suggests that inclusion of Google Scholar, often criticized for uncertainty of quality, did not skew the overall findings.

A breakdown by publication type revealed that 95.24% of studies were journal articles and only 4.76% book chapters. Excluding book chapters from analysis did not alter basic patterns in publication trends, thematic distributions, or quality ratings to any considerable degree. This confirms the supremacy of peer-reviewed journal articles as the backbone of quality research in nutrient dynamics. Where stratified by year of publication, peak productivity years (2017, 2023, 2021) showed a modest increase in reporting more advanced modeling approaches and better Newcastle-Ottawa quality scores. However, removing outlier years to examine (like 2017 with 15 studies) did not notably affect global patterns in nutrient focus or methodology used. Outcomes thus appear fairly consistent over time, despite different yearly rates of research activity. Elimination of leading contributor countries, China (26 studies) and the USA (15 studies), from the dataset caused only small changes in thematic percentages, for example, the reduction in algal bloom and biogeochemical process studies. Global uniformity in addressing nutrient pollution and modeling, however, confirms a general cross-national consensus about top research themes, implying outcomes are not inappropriately biased by regional overrepresentation.

High-quality papers (6-7 stars, 40 studies) were also analyzed independently and reflected a larger predominance of multi-nutrient analysis, long-term monitoring of ecosystems, and advanced modeling. Exclusion of low- and moderate-quality studies did not alter the main conclusions about nitrogen and phosphorus being the dominating eutrophication drivers. Their exclusion did decrease methodological heterogeneity and highlight the policy-relevance role of high-quality evidence. Research with only elementary statistical analysis (36 studies) was compared to research incorporating regression, computer modeling, or experiments (cumulative of 22 studies). Sophisticated methods yielded more accurate findings of nutrient interactions and often supported policy inferences with higher confidence. However, the overall inferences - of nutrient loading effects and the need for watershed management holistically, were robust by method.

3.6. Reporting Biases

Risk of reporting bias among the included studies was assessed in terms of selective outcome reporting, publication bias, and methodological reporting transparency. While the majority of high-quality studies reported well a good description of aims, data collection processes, and analysis frameworks, differences were observed in consistency in reporting, particularly on the rationale for study limitations or project termination. In a few cases, contextual factors underlying outcomes were not reported or explained poorly.

Most salient was a trend towards publication bias in favour of developed world studies where effective intervention methods were outlined and unequivocal evidence of failure or resource limitation-based limitations was clearly delineated. Less overtly were the developing country studies occasionally ambiguous in causes and nature of failed or aborted endeavours, corresponding uneven reporting standards geographically.

Sparse representation was also found in individual termination themes evidence, including suspension, integration, or redirection, suggesting the need for inclusion of more general criteria in future reviews to allow a more comprehensive range of nutrient management outcomes to be captured. Despite these restrictions, the systematic review combined a broad range of sources, types of studies, and methodological designs and therefore minimized the chance of broad systematic reporting bias.

3.7. Certainty of Evidence

Quality of evidence for macronutrient regulation in freshwater and terrestrial ecosystems was graded on major methodological criteria of precision, directness, and consistency for the 82 studies reviewed. The Newcastle-Ottawa Scale graded 40 of 82 studies as high quality (48.8%), indicating the quality of their evidence. Experiments carefully designed, accurate quantitation of nutrients, and large-scale ecological analysis often with multi-nutrient experiments and long-term monitoring, characterized high quality studies. The other 45.1% of the studies were of medium quality (37 studies), very useful to nutrient dynamics but not in the sense that they were incomplete in terms of information or poorly designed and therefore lost general validity. Just a minority of 6.1% (5 studies) was of poor quality, essentially due to small-scale experimentation, short-term monitoring, or methodological issues.

In spite of a degree of heterogeneity, notably in lower infrastructure or resource districts, the general evidence base is strong. The variety of study settings and thematic scope (e.g., nutrient removal, algal blooms, water quality monitoring) lead to an equitable and internationally applicable

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understanding of nutrient-related issues. Relatively small problems of risk of bias in an extremely limited number of studies do not significantly detract from overall confidence in findings. The strength of evidence is deemed moderate to high and provides a good foundation for policy informing, guiding ecosystem management practices, and informing future research on regulation of nutrients. More high-quality, empirically informed research is needed, however—particularly in understudied areas—to support generalizability and policy relevance of existing findings.

4. Discussion

4.1. Interpretation of Findings in the Context of Prior Studies and Working Hypotheses

The research examination tracked IoT technology implementations which monitor and manage the vital macronutrients N, P, and C through different ecological frameworks and applications. Data indicates that IoT applications dominate two major environmental sectors: first nutrient pollution sectors (52.38%) and second ecological disintegration areas such as eutrophication and harmful algal blooms (25.00%). The fundamental nutrient imbalance processes affect water systems, but they apply equally to soil systems and agricultural land as well as atmospheric releases and industrial environmental releases.

Research has demonstrated that nitrogen and phosphorus represent the main components causing environmental disintegration which spreads through agricultural field runoffs and atmospheric deposits and wastewater discharges. The small proportion of studies concerning wastewater treatment combined with direct nutrient management at 1.19% appears unexpected because these methods represent targeted sources of macronutrient pollution. This situation suggests that either research is insufficient at present or the effort to convert technological solutions to direct source-based solutions needs more investment.

21.43% of analyzed research aligns "Other" due to emerging integrative methods involving appropriate farming, carbon circulation modeling, and off-site soil nutrient examination to demonstrate Internet of Things capabilities outside water-related uses. The scientific worth of IoT for nutrient dynamics measurement spans across all structural and temporal scales (11.90% for Water Quality Monitoring & Modelling and 9.52% for Ecological Processes) regardless of medium.

4.2. Limitations of the Evidence Included in the Review

The reviewed evidence mainly focuses on well-established settings from the Global North world. These frameworks show limited potential to apply at low- and middle-income nations where nutrient mismanagement problems remain unresolved. Several research efforts only focus on temporary prototype assessments without proper evaluation of system efficiency alongside data accuracy and convenience during extreme field conditions.

Another issue is methodological variation. Multiple features of IoT platforms including sensor specifications and calibration techniques and data analytic implementations cause impediments to sharing and scaling across different contexts. Most research fails to present expense estimations and scalability predictions that would enable better understanding of large-scale practical implementation.

4.3. Limitations of the Review Process Used

This review used systematic practices with Newcastle-Ottawa Scale quality assessment but still contains typical limitations because of its nature. The review apparently failed to identify relevant sources located inside informal literature or non-English language items. Mixed results in studies tend to receive little publication because of publication bias.

The assignment of studies into distinct thematic categories needed interpretive judgment since some research incorporated multiple domains (farm pollution affecting aquatic ecosystems). The researchers minimized subjectivity by taking steps to prevent minor inconsistencies from arising in the thematic proportions.

4.4. Implications for Practice, Policy, and Future Research

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The results demonstrate that Internet of Things (IoT) technology offers extensive potential to handle macronutrient system dynamics across agricultural settings and wastewater activities and environmental protection and industrial monitoring sectors. The implementation of IoT sensing provides real-time measurement capabilities which enables accurate nutrient application and enhances loss reduction while permitting swift remedial actions leading to higher production output along with enhanced environmental stewardship. Executive and inspirational systems should receive IoT-derived nutrient data to create three policy programs which include precision fertilizer subsidies together with nutrient trading schemes along with watershed protection programs. The implementation of this approach would lead to transparent systems as well as accountable ecosystems with active management.

Future research needs to follow four main objectives which include expanding IoT implementations into under included regions combined with developing low-implementation lower-cost sensor systems alongside examining the long-term durability of IoT infrastructure and integrating IoT collected data into decision-support systems along with machine learning platforms to enhance future nutrient management capabilities. Monitoring carbon should become a higher priority because it pertains to soil respiration levels and land-use transitions and their effects on climate.

The present IoT applications demonstrate impressive achievements when monitoring macronutrients yet a comprehensive proactive strategy needs establishment. The implementation approach needs both technological progressions together with policy development that includes everyone and environmentally sustainable infrastructure development.

5. Conclusions

This systematic review analyzed 82 peer-reviewed studies published between 2015 and 2025, evaluating the application of Internet of Things (IoT) technologies for monitoring key macronutrients—nitrogen (N), phosphorus (P), and carbon (C)—in agricultural and aquatic environments. The majority of studies focused on nutrient pollution and removal (52.38%), followed by eutrophication and algal blooms (25.00%), while research on wastewater treatment (1.19%) and biogeochemical processes (9.52%) remained limited. China (31.70%) and the United States (18.30%) were the leading contributors, reflecting strong national investments in nutrient management. Nitrogen and phosphorus monitoring was primarily conducted using general concentration measurements (55.95% and 54.76%, respectively), while advanced techniques such as nutrient speciation and removal efficiency analysis were underrepresented. Carbon monitoring exhibited the highest inconsistency, with 79.76% of studies reporting undefined or variable metrics. Technological reporting was a major shortfall: 75% of studies did not specify microcontrollers or cloud platforms, and 70.24% omitted connectivity protocols. Where disclosed, Arduino-based systems and Wi-Fi were most frequently used. Statistical modeling was employed in 42.86% of studies; however, one-third of the literature lacked any model performance metrics. Some systems reported accuracy rates up to 98%, indicating strong technical potential for IoT-based nutrient sensing. Quality assessments revealed that 48.8% of studies were of high methodological quality, 45.1% moderate, and 6.1% low. Sensitivity and subgroup analyses confirmed greater sensor accuracy in aquatic systems using optical sensors and highlighted methodological disparities between developed and developing countries. Despite reporting gaps and implementation barriers, IoT technologies demonstrate high potential for real-time, high-resolution monitoring of macronutrients. To support broader adoption, future research should prioritize standardization, low-cost sensor development, integration with AI and cloud platforms, and increased investment in capacity-building, particularly in under-resourced regions. This review provides a strategic foundation for scaling IoT-enabled nutrient management systems globally.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Compressive Overview of Macronutrients – Eutrophication Control Approaches.

Ref.	Year	Research Focus	Methodology	Key Outcomes	Challenges Identified	Recommendations
Li et al. (2025)	2025	Seasonal variations and drivers of TN and TP in surface waters	Regression & Advanced Modeling Techniques	Analyzed spatial and temporal distribution of TN and TP in China's surface waters; highlighted human and natural influence	Not specified	Not provided
Paerl et al. (2016)	2016	Dual nutrient (N & P) reductions to prevent eutrophication	Statistical Analysis & Modeling	Phosphorus reduction alone insufficient; dual N & P reductions needed to mitigate eutrophication and HABs	Not specified	Target both N & P simultaneously in lake management plans
Pishbin et al. (2021)	2021	Efficiency of microalgae in removing N and P from wastewater	Engineering Design; Regression & Advanced Modeling	Synechococcus elongatus removed 87.4% nitrogen and 85.1% phosphorus under mixotrophic conditions	Not specified	Use mixotrophic microalgae for eco-friendly dairy wastewater treatment
Mitsch (2017)	2017	Restoration of Great Black Swamp to reduce P in Lake Erie	Statistical & Computational Modeling	Wetland restoration could reduce phosphorus by up to 40% in Maumee River Basin	Not specified	Adopt phased wetland restoration with demonstration projects before full-scale implementation
Martin et al. (2020)	2020	Reducing nutrient loads in agricultural watersheds	Statistical Analysis & Modeling; Sensor Integration	Controlled fertilizer application and wetland restoration reduce eutrophication with 89% prediction accuracy	Seasonal variability affects strategy efficiency	Implement precision agriculture and seasonally adaptive measures
Elser et al. (2019)	2019	Global nutrient limitation patterns in lakes	Regression & Advanced Modeling Techniques	62% lakes P-limited, 25% N-limited, 13% co-limited; management should consider local limitation types	Not specified	Tailor eutrophication control based on site-specific nutrient limitation
Gu et al. (2020)	2020	Impact of cyanobacteria on P cycling and aquatic ecosystems	Experimental & Computational Modes	Cyanobacteria absorb more P than macrophytes; excess P (>1.0 mg/L) suppresses growth; toxins harm biota	Not specified	Monitor cyanobacteria and manage P to control eutrophication
Mielcarek et al. (2024)	2024	Nutrient management in	Not specified	Closed-loop systems improve nutrient	Uncontrolled discharge	Research on optimizing nutrient

		soilless cultivation systems		recovery and reduce pollution	of drainage water	recirculation techniques
Wang et al. (2021)	2021	Harmful algal blooms (HABs) in Chinese coastal waters	Regression modeling using MATLAB and R; analysis of nutrient ratios	85% accuracy in predicting HAB occurrences; high N:P ratios (>25) correlate with increased HAB frequency; projections indicate worsening conditions even under sustainability scenarios	Excess nitrogen loading since the 1980s; imbalance in nutrient ratios	Implement nutrient reduction strategies focusing on nitrogen control; enhance monitoring of nutrient inputs
Kaushal et al. (2017)	2017	Nitrogen and phosphorus budgets in urban watersheds	Statistical analysis and modeling using programming languages and statistical software	92% accuracy; urban watersheds contribute significantly to nutrient pollution, with nitrogen inputs much higher than phosphorus	High nitrogen surplus from urban runoff; household activities like lawn fertilization and pet waste contribute to nutrient loads	Develop targeted nutrient management strategies focusing on reducing nitrogen surplus; promote public awareness on household contributions to nutrient pollution
Tang et al. (2016)	2016	Effects of external nutrient reductions on algal blooms in Lake Taihu, China	GIS and hydrological modeling; regression and advanced modeling techniques	Up to 38% reduction in chlorophyll-a with 50-84% nutrient reduction; phosphorus identified as the primary limiting factor	Need for additional ecological restoration measures beyond nutrient reduction	Combine nutrient reduction with ecological restoration efforts; prioritize phosphorus control during summer months
Bergbusch et al. (2021)	2021	Effects of nitrogen removal from waste-water on phytoplankton in eutrophic prairie streams	Regression and advanced modeling techniques using programming languages and statistical software	69%-79% accuracy; nitrogen removal by biological nutrient removal (BNR) technology reduced phytoplankton abundance by 52% and shifted community composition	Limited impact on phosphorus levels; need for comprehensive nutrient removal	Implement comprehensive nutrient removal strategies addressing both nitrogen and phosphorus; monitor shifts in phytoplankton communities
Wurochekke et al. (2021)	2021	Nutrient removal from artificial bathroom greywater by phycoremediation using Botryococcus.	Experimental and computational modes	Nitrate removal reached 97%; phosphate removal up to 87% over 30 days	Scalability and long-term efficiency of phycoremediation	Explore large-scale applications of phycoremediation; assess long-term

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						sustainability and efficiency
Payen et al. (2021)	2021	Spatially explicit fate factors for nitrogen and phosphorus emissions at the global scale	GIS and hydrological modeling; statistical analysis and modeling	94% accuracy; developed spatially explicit fate factors for both nitrogen and phosphorus; emphasized importance of high-resolution river basin data	Traditional models often consider phosphorus as the sole limiting factor	Incorporate both nitrogen and phosphorus in eutrophication impact assessments; utilize high-resolution data for accurate modeling
Xiao et al. (2017)	2017	Nutrient removal f rom Chinese coastal waters by large-scale seaweed aquaculture	Not specified	Seaweed aquaculture removes significant nutrients, mitigating coastal eutrophication	Quantifying the exact impact of seaweed aquaculture on nutrient removal	Promote large-scale seaweed aquaculture as a nutrient mitigation strategy; conduct further research to quantify its effectiveness
Lapointe et al. (2015)	2015	Sewage-driven eutrophication and algal blooms in Florida's Indian River Lagoon	Regression and advanced modeling techniques using MATLAB and R	89% accuracy in predicting nutrient-induced algal blooms; high nitrogen and phosphorus levels from septic system leakage and storm water runoff contribute to harmful algal blooms	Excess nutrients from human activities degrade lagoon water quality	Improve sewage treatment infrastructure; implement storm water management practices to reduce nutrient runoff
Hossain et al. (2019)	2019	Nutrient management and structural shifts in fish assemblages in Lake Ontario	Regression and advanced modeling techniques	94% and 88% accuracy; long-term phosphorus reductions led to fish community shifts, reducing total fish biomass per unit of total phosphorus	Further phosphorus reduction may cause a 24% decline in fish biomass, affecting key species	Balance nutrient reduction efforts with ecological considerations; monitor fish community responses to nutrient management
Mennaa et al. (2015)	2015	Urban wastewater treatment by seven species of microalgae and an algal bloom	Not specified	Microalgae species efficiently remove nitrogen and phosphorus, with high biomass productivity	Optimization of microalgae species for maximum nutrient removal	Identify and cultivate microalgae species with high nutrient removal efficiency; integrate microalgae-based treatment in urban wastewater management

Chen et al. (2017)	2017	Tracking nitrogen sources, transformation, and transport at a basin scale with complex plain river networks	Statistical analysis and modeling using programming languages and statistical software	88% accuracy; identified point and nonpoint sources of nitrogen pollution; seasonal variations affect nitrogen transport	Long-term agricultural pollution control is essential to combat eutrophication	Implement long-term agricultural best management practices; monitor seasonal variations in nitrogen transport
Park et al. (2020)	2020	Advances in ICT and sensor technology for monitoring water quality	Statistical analysis and modeling using programming languages and statistical software	96.4% accuracy; reviewed advancements in ICT and sensor technology for real-time water quality monitoring	Integration of ICT and sensor technology in existing water quality monitoring frameworks	Develop and implement ICT-based real-time water quality monitoring systems; ensure compatibility with existing infrastructure
Kumar et al. (2024)	2024	AI-driven nutrient removal in algae-based systems	AI/ML models (ANN, RF) and lab experiments	AI models achieved 99.87% accuracy in predicting optimal algal growth for maximum nutrient removal	Requires extensive training data; high computational power needed	Integrate AI with real-time sensor networks.
Martínez et al. (2020)	2020	Portable nitrate/nitrite monitoring	Electrochemical sensors Arduino and MATLAB/R validation	Sensor showed 93% accuracy compared to standard lab methods	Sensors required frequent calibration in field conditions	Use automated calibration protocols.
Watson et al. (2016)	2019	Coastal algal blooms	Electrochemical sensors and ESP8266, Wi-Fi and cloud analytics	Established correlation between N:P ratios and bloom intensity (87.5% accuracy)	Marine organisms fouled sensors, reducing accuracy over time	Apply anti-fouling coatings to sensors for long term deployment.
Manahan (2018)	2018	Nutrient cycling in aquatic systems	Optical/chemical sensors and Arduino and statistical modeling	Found agricultural runoff accounts for more than 60% of nutrient imbalances	Sensor interference from organic matter	Combine multiple sensor types to improve measurement accuracy.
Álvarez et al. (2017)	2017	Watershed nutrient pollution	GIS and hydrological modeling	Agriculture and sewage caused more than 90% of nutrient loads in studied watershed	Difficult to track non-point source pollution	Implement buffer zones and precision farming techniques
Wurtsbaugh et al. (2019)	2019	Dual-nutrient (N/P) reduction	Meta-analysis and DPSIR framework	95% Nitrogen and 90% Phosphorus reduction needed to control blooms.	Current policies focus on single nutrients	Establish cross-sectoral nutrient quotas addressing both N and P
Xiao et al. (2017)	2017	Seaweed aquaculture for N/P removal	Not specified	Calculated 75,000 tons nitrogen	Space competition with	Create incentives for offshore

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				removed annually by current farms	commercial fishing operations	seaweed farming zones
Tiwari and Pal (2022)	2022	Mapped nutrient contamination hotspots in river ecosystems	IoT-enabled spectrophotometry with ESP8266 microcontrollers	Identified industrial/agricultural hotspots (91% N, 85% P accuracy)	Nutrients released from sediments during floods	Combine dredging with phytoremediation strategies
Martínez et al. (2020)	2020	IoT system for wastewater nitrate monitoring	Teensy 3.6 microcontroller with GSM/GPRS transmission to cloud	Showed strong correlation with lab results in real-time monitoring	Limited power supply in remote monitoring locations	Develop solar-powered sensor nodes for off-grid use
Daigavane and Gaikwad (2017)	2017	IoT water quality sensors for parameter estimation	ESP32 chips with LoRa wireless transmission to cloud services	Achieved 90% accuracy in estimating key water quality parameters	Experienced data transmission delays in some conditions	Implement edge computing to reduce latency in analysis
Lapointe et al. (2015)	2015	Phosphorus-driven eutrophication	Optical sensors and Arduino and long-term monitoring	Phosphorus from detergents/sewage increased blooms 2.4–2.7times.	Legacy Phosphorus in sediments.	Ban Phosphorous in detergents and sediment caps.
Shen et al. (2015)	2015	Microalgae for wastewater treatment	Experimental & Computational Modes	Scenedesmus removed 83.5% Ammonium ion, 57.9%Phosphate ion.	Low Nitrate ion removal (39%).	Genetic engineering of algal strains.
Nankya et al. (2019)	2019	Agricultural nutrient management	Surveys and statistical analysis (SPSS)	Poor practices led to 52% Nitrogen/Phosphorus loss in Uganda.	Farmer adoption barriers.	Use subsidies for sustainable fertilizers.
Eom et al. (2016)	2016	Wastewater Nitrogen removal limitations	Experimental & Computational Modes: Lab-scale BNR reactor tests	BNR reduced N but not dissolved organic N (DON).	DON persistence in effluents.	Combine BNR with advanced oxidation.
Znachor et al. (2020)	2020	Phytoplankton response to nutrients	Experimental & Computational Modes	89% accuracy of diatoms dominated under Phosphorus limitation	Climate change interactions.	Implement adaptive Phosphorus reduction strategies.
Nandakumar et al. (2019)	2019	Wetland N/P removal	Not specified	Brachiaria mutica achieved 82% Phosphorus removal.	Winter efficiency drops.	Introduce hybrid wetland designs for cold climates.
Shang et al. (2023)	2023	Remote water quality monitoring	Statistical Analysis & Modeling: Sentinel-2 and XGBoost ML model	Predicted Chlorophyl-a concentration and ammonium concentration with 90–73% accuracy	Cloud cover disrupting satellite data.	Combine satellites with ground sensors.
Hendriks and Langeveld (2017)	2017	Flexible WWTP nutrient standard	Regression & Advanced Modeling Techniques MATLAB/R and	Achieved 89% accuracy and Dynamic Nitrogen to Phosphorus (N:P)	Regulatory resistance.	Pilot adaptive permit systems.

			scenario modeling	ratio control reduced blooms.		
Tiwari and Pal (2022)	2022	River eutrophication mitigation	Statistical Analysis & Modeling: Field sampling and spectrophotometry	95.3% nutrient impact from point sources.	Enforcement gaps.	Introduce stricter industrial discharge permits.
Strokal et al. (2015)	2015	Pearl River nutrient modeling	Statistical Analysis & Modeling: SPARROW model and sub-basin analysis	Agriculture contributed 71% of Nitrogen and 92% of Phosphorus loads.	Data scarcity in rural basins.	Expand monitoring networks.
Amit Kumar Tiwari and Dan Bahadur Pal. (2022)	2022	Nutrient contamination & eutrophication in river ecosystems	Eutrophication in river ecosystems Literature review, empirical referral case referreferences	Eutrophication causes oxygen depletion, algal blooms, loss of biodiversity, water quality decline	Anthropogenic nutrient runoff, industrial waste, lack of awareness, inadequate regulation	Reduce fertilizer use, control runoff, improve wastewater treatment, increase awareness & monitoring
Strokal et al. (2015)	2015	Nutrient export (N & P) and eutrophication in Pearl River basin	Sub-basin scale modeling using Global NEWS-2 (1970–2050), scenario analysis, and model validation	Nitrogen and phosphorus exports doubled since 1970; agriculture and sewage drive increases.	Rapid urbanization, intense agriculture, poor management, limited treatment, and uncertain socioeconomic future.	Prioritize downstream nutrient management, improve sewage treatment, reduce agricultural inputs, enhance monitoring and policies.
Lin, Tsai and Lyu. (2021)	2021	Wireless IoT multi-sensor system monitors aquaculture water quality and mining impacts in Saudi SMEs.	Designed and implemented ESP32 multi-sensor system with pH, DO, EC, temperature sensors; tested 20 days in situ	Achieved reliable real-time monitoring of water temperature, pH, dissolved oxygen, conductivity, and salinity for aquaculture.	Sensor drift, contamination risk, maintenance required, dependence on stable Wi-Fi connection.	Regular calibration, maintenance, self-cleaning design, expandability for diverse aquaculture and long-term use.
Suresh et al. (2023)	2023	Advancements in water quality indicators for eutrophication in global freshwater lakes	Reviewed literature; used DPSIR framework; developed causal network linking 58 indicators in seven themes.	Emphasized holistic indicators climate, land use, socioeconomics and developed causal network showing system feedbacks.	Lack of integrated monitoring, poor ecosystem modeling, limited data, fragmented assessments, especially in developing regions.	Expand monitoring, link land use, combine satellite data, model nutrients, and promote interdisciplinary management.

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Hua et al. (2023)	2023	Impact of upgrading protected areas (PAs) on conservation effectiveness in the Tibetan Plateau	Used propensity score matching, NDVI trend analysis, and empirical case studies.	Upgrading protected areas reverses decline; nine of eleven showed improved vegetation growth.	Infrastructure growth, overgrazing, funding shortages, livelihood conflicts, and climate change impacts	Reduce fertilizer use, control runoff, improve wastewater treatment, increase awareness & monitoring
Han et al. (2021)	2021	Nutrient source analysis in phosphorus-rich watershed	SWAT modeling, scenario analysis	Crop production caused 66% N, 87% P; N is limiting nutrient	Legacy phosphorus, overfertilization, poor rural treatment	Cut N 60%, stop P, manage sources, consider legacy impacts
Chemical Lake Restoration. (2021)	2021	Eutrophication causes, internal phosphorus cycling, and impacts on lake ecosystems	Comprehensive literature review, case studies	Eutrophication from phosphorus causes algal blooms, oxygen loss, and delayed lake recovery.	Internal phosphorus loading and algal blooms slow recovery, causing ecological and economic losses.	Combine prevention and treatment, manage sediments, apply circular economy, and improve policy coordination.
Wu et al. (2017)	2017	Pyropia yezoensis and Ulva species effectively remove nutrients in offshore aquaculture systems.	Field biomass measurement, nutrient analysis, remote sensing, and statistical analysis were used in the study.	Pyropia removed 3688 tons nitrogen and 106 tons phosphorus; Ulva removed 77 tons nitrogen and 3 tons phosphorus.	High nutrients from agriculture and aquaculture; limited Ulva use and market; Pyropia seasonal limits.	Promote Ulva use, add heat-tolerant seaweeds, integrate harvesting in nutrient management.
Liang et al. (2015)	2015	Nutrient removal efficiency using rice-straw in denitrifying bioreactor	Pilot experiment comparing woodchip media, nutrient loading rates, and hydraulic retention times.	At medium nutrient load (24-hour retention), rice-straw removed more nutrients than woodchips.	Rice-straw outperforms woodchips at medium load; high load reduces efficiency and raises TOC risk.	Use rice-straw at medium nutrient loads with 24-hour retention; monitor organic carbon; woodchips for low loads..
Zhu et al. (2024)	2024	Advances in on-site spectrophotometric nutrient measurement in aquatic ecosystems	Comprehensive review (2019–2023) covers flow analysis, lab-on-chip, smartphone, and microfluidic nutrient detection systems.	Reviewed 40+ sensors with nanomolar to micromolar detection; lab-on-chip and smartphones enable low-cost monitoring	Challenges: variability, degradation, sensitivity, interference, lack of standards, no ammonium references.	Improve standards; enhance sensing; integrate AI and IoT; develop ammonium references; support collaborations.

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Fernandes et al. (2017)	2017	Ecological optimization of N:P recovery from blackwater using microalgae	Lab experiment using *Chlorella sorokiniana* in photobioreactors across N:P ratios (15–26)	Phosphorus recovered in 4 days, nitrogen 75% in two weeks, biomass 12 g/L	Delayed nitrogen removal enlarges system; N losses as ammonia and nitrous oxide.	Use high N:P species or mixtures; apply eco-stoichiometry; select resilient species for treatment.
Andersen et al. (2019)	2019	Seasonal nutrient limitation of algal groups in a hyper-eutrophic reservoir	Weekly experiments, nutrient additions, N-form tests, sampling	Seasonal shifts: spring P-limit, summer N-limit; taxa show N-form preferences	Variable nutrient sources, fish excretion, storm-driven nutrient changes	Manage both N and P; include N form; improve internal nutrient control
Smith, King and Williams. (2015)	2015	Causes of algal blooms in Lake Erie	Review of literature and agricultural trends	Increased soluble Phosphorus drives harmful algal blooms	Climate shifts, poor fertilizer timing, soil layering, drainage, large farm sizes	Revise fertilizer guidelines, control runoff, target phosphorus at landscape level
Morales-Marín, et al. (2017)	2017	Nutrient loading in prairie reservoir	Catchment modeling using SPARROW	High nutrient retention; fertilizer is major nutrient source	Agricultural runoff, population growth, reservoir limitations	Optimize land use, reduce inputs, improve monitoring
Diaz-Elsayed et al. (2017)	2017	Sustainability of onsite wastewater treatment	Life cycle and cost assessments	Advanced systems remove more nitrogen, lower eutrophication	High costs, material and energy use, variable performance	Use efficient designs, sustainable materials, reduce maintenance
Alazaiza et al. (2023)	2023	Microalgae-based sewage water treatment	Experimental, various mixing ratios, biomass tracking	97% phosphorus, 95% nitrogen, 84% organic removal, biomass yield	Light limitation, cost, scalability, pH, temperature control.	Optimize conditions, integrate systems, improve harvesting methods
Liu et al. (2025)	2025	Eutrophication in separated urban ponds	Field sampling, phosphorus analysis, water testing	High phosphorus, Class V water, Fe/Al-P main eutrophication source	Sediment pollution, sewage input, poor circulation, ineffective treatment	Remove silt, plant submerged vegetation, divert and treat sewage
Chen et al. (2017)	2017	Phytoremediation of nutrient-polluted drainage	Pot experiment with five plant species	LS removed 57.7% nitrogen, 57.3% phosphorus; high plant uptake	Poor growth of some species, limited scalability, root decay	Use LS, OS, IA; harvest on time; test in real field conditions
Ma, Huang and	2018	Gate management impact on river water	WASP modeling with hydrology	Gate opening raises BOD,	High pollution load, tidal	Limit gate open time, simulate effects,

Kao. (2018)		quality	and pollution data	ammonia; 5 days to self-recover	effects, system sensitivity	optimize closure strategy
Vymazal & Kröpfelová (2015)	2015	How hydraulic loading and seasonality affect nutrient removal in free-water-surface constructed wetlands	Monitored N and P removal in a temperate free-water-surface wetland across seasonal hydraulic load rates	Removal rates ranged 4–12 g P m⁻² yr⁻¹ and 50–75 g N m⁻² yr⁻¹, peaking in summer	Seasonal cold and high flows reduced performance	Adapt hydraulic loading seasonally to optimize removal vs.
Shuet et al. (2018)	2018	Nutrient removal by Chlorella vulgaris and Scenedesmus quadricauda in batch reactors	Operated batch algal reactors with municipal wastewater; tracked NH_4–N, NO_3–N, PO_4 removal kinetics	S. quadricauda removed 84 % NH_3–N, C. vulgaris 77 % TN; PO_4 removal < 50 %	Both strains limited in NO_3–N and PO_4	Employ mixed-strain consortia and kinetic modeling to boost uptake rates
Pedersen & Borum (2016)	2016	Nutrient removal via biomass accumulation on artificial substrata in the northern Baltic Sea	Deployed artificial substrates in situ for 14.5 months; quantified accumulated N, P in biomass	Substrata biomass sequestered ~50 g N m^{-2} and 5 g P m^{-2} primarily in invertebrate and algal biomass	Heavy-metal uptake by biomass limits its use as soil amendment	Locate substrata near point sources and valorize biomass for bioenergy
Mao et al. (2020)	2020	Quantification of N and P removal by China's seaweed aquaculture	Combined national seaweed production statistics with tissue N/P content to estimate total nutrient sink	China's seaweed farms removed ~75,000 t N and 9,500 t P in 2010	Expansion constrained by market incentives and profitability	Support seaweed farmers through policy incentives and integrate aquaculture into eutrophication management
Meng et al. (2020)	2020	IoT/cloud-based potassium sensor for real-time water quality	Developed an ion-selective electrode for K^+ linked via MQTT to a cloud platform; validated against lab assays	Sensor achieved R^2 = 0.992 vs. lab standards; detection limit 0.1 mg L^{-1}	Electrode fouling requires frequent calibration	Integrate self-cleaning membranes and remote calibration routines
Dodds et al. (2018)	2018	Review of N and P roles in stream eutrophication and management implications	Meta-analysis of global stream nutrient–chlorophyll datasets; developed trophic state classification thresholds	Defined thresholds where TN > 2 mg L^{-1} or TP > 0.05 mg L^{-1} drove periphyton blooms; dual N+P	Overlooking N control leads to persistent cyanobacteria	Manage both N and P in stream catchments simultaneously
Liet al.(2017)	2017	Advanced tertiary treatment of wastewater with Desmodesmus sp. SNN1	Batch culture optimization of pH and inoculum density for municipal	Achieved ~90 % TN, 95 % TP and ~100 % NH_4^+ removal within 12 days	Maintaining elevated pH operationally challenging	Deploy Desmodesmus in tertiary ponds and valorize algal biomass

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			secondary effluent polishing			
Wang & Lü (2015)	2015	Impact of pyrolysis temperature on nutrient retention in poultry litter biochar	Produced biochar at 300 °C and 500 °C; characterized nutrient availability and sorption properties in lab assays	Higher-temperature biochar (500 °C) had greater C stability but reduced P availability; 300 °C char released more labile	Trade-off between nutrient stabilization and availability	Apply 500 °C biochar with co-amendments to balance P retention and release
Fu et al. (2022)	2022	Warming and acidification effects on Heterosigma akashiwo cellular composition	Cultured under current vs. elevated T (+4 °C) and pCO_2 (1000 µatm); measured cellular C, N, P, DNA/RNA content	Future climate reduced cellular C, N, P and nucleic acids by 30–36 %, indicating potential bloom declines	Species-specific responses complicate projections	Incorporate multispecies experiments into climate–eutrophication models
Paerl & Huisman (2021)	2021	Global trends in harmful cyanobacterial blooms driven by climate change	Synthesized > 200 satellite and in situ bloom records (2003–2007); correlated bloom frequency with SST and nutrient loads	Bloom frequency increased ~2 % yr^{-1}; warming strongest	Distinguishing climate vs. nutrient driverse	Strengthen long-term monitoring and coupled climate–nutrient models
Wu et al. (2021)	2021	IoT-based dissolved oxygen monitoring for river basins	Deployed wireless microcontroller DO sensors linked via NB-IoT to cloud; validated against YSI sondes	Enabled continuous DO profiles with error < 0.15 mg L^{-1}; supported remote data visualization	Field connectivity and power supply consistency	Integrate solar power and mesh networking for robust basin-scale DO monitoring
Zhou et al (2017)	2017	Effects of CAS vs. BNR wastewater effluent on algal bloom potential	Bioassays exposing freshwater algal communities to CAS (conventional activated sludge) vs. BNR (biological nutrient removal) plant effluents	BNR effluent triggered higher N-based algal yield despite lower TN, due to more bioavailable forms	Variability in nutrient speciation alters downstream effects	Evaluate effluent bioavailability before implementing full-scale BNR conversion
Mehta et al. (2015)	2015	River–lake connectivity effects on sediment C:N:P ratios in large lakes	Sampled sediments from 82 lakes; compared C:N:P stoichiometry in connected vs. isolated systems using elemental analysis	Connected lakes had higher sediment P; isolated lakes showed greater C and N accumulation; eutrophication reduced carbon sequestration	Heterogeneity in connectivity and hydrodynamics	Tailor sediment management to connectivity context (e.g., dredging vs. biomanipulation)
Kim et al. (2018)	2018	Smart IoT water-monitoring system for pH, CO_2, water level	Built ARM-based sensor nodes measuring pH, temperature, CO_2	Real-time monitoring with < 5 min latency; automated malfunction alerts	Scaling across multiple sites challenged by	Employ LPWAN protocols and edge

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			and level; cloud integration with alert functions		network bandwidth	computing for scalable, low-power deployments
Zhang et al. (2020)	2020	Microbial community response to nutrient removal in coastal sediment using ecological concrete	Embedded eco-concrete aggregates in nutrient-rich sediments; tracked microbial 16S rRNA gene abundances and TN/TP removal over 28 days	Eco-concrete promoted denitrifying bacteria (e.g., Sulfurovum); achieved ~8 % TN, 8 % TP removal	Low overall removal efficiency; substrate performance varied	Optimize eco-concrete formulations and support targeted microbial colonization
Wu et al. (2016)	2016	Phytoremediation of eutrophic waters by paired emergent vs. submerged macrophytes	Paired plantings of Thalia dealbata, Canna indica (emergent) and Vallisneria natans (submerged) in waters high in N, P or both; measured uptake and biomass over 30 days	Dual emergent–submerged combinations removed nutrients more effectively; T. dealbata + C. indica best for TN, NH_3–N, NO_3–N and TP removal	Site-specific species performance; optimal pairings vary with nutrient profile	Design phytoremediation schemes tailored to dominant nutrient stress (N, P or mixed)

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