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Artificial Intelligence for Constructed Wetlands: Toward Intelligent, Adaptive, and Autonomous Treatment Systems

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Abstract: Constructed wetlands (CWs) represent one of the most sustainable and cost-effective nature-based solutions (NBS) for wastewater treatment. However, their dynamic biogeochemical processes and sensitivity to fluctuating environmental and operational conditions pose major challenges for prediction, optimization, and control. Conventional design and modeling approaches, whether empirical or mechanistic, often fail to capture the nonlinear interactions governing CW performance. In recent years, the convergence of CW research with Artificial Intelligence (AI) and Machine Learning (ML) has introduced transformative opportunities for intelligent, adaptive, and autonomous wastewater management. This critical review synthesizes the state-of-the-art applications of AI in CWs, encompassing four major domains: (i) predictive modeling of effluent quality, (ii) process monitoring and fault detection, (iii) optimization of design and operational parameters, and (iv) forecasting and real-time adaptive control. The review highlights the superior predictive accuracy and data-driven adaptability of AI models such as Artificial Neural Networks, Support Vector Machines, and tree-based ensemble methods compared to traditional statistical tools. It also examines emerging hybrid frameworks that couple AI with mechanistic models and fuzzy logic systems to enhance interpretability and robustness. Key challenges are identified, including data scarcity and inconsistency, limited model generalizability, and the lack of standardized validation protocols. Future research should prioritize the development of open-access, high-quality long-term CW datasets, the integration of Explainable AI (XAI) and transfer learning to improve transparency and scalability, and the advancement of hybrid and closed-loop control architectures for fully automated "intelligent wetlands." Collectively, this review positions AI as a cornerstone technology driving the next generation of smart, resilient, and sustainable constructed wetland systems.

Keywords: Constructed wetlands, Artificial intelligence (AI), Machine learning (ML), Intelligent wetlands, Wastewater treatment, Predictive modeling.

I. Introduction

The global water crisis, exacerbated by population growth, industrialization, and climate change, demands a paradigm shift towards sustainable and resilient water treatment technologies. In this context, Constructed Wetlands (CWs) have emerged as a cornerstone of nature-based solutions (NBS) for wastewater remediation. These engineered systems mimic the processes of natural wetlands, utilizing complex interactions between substrate, macrophytes, and microbial communities to remove pollutants from municipal, industrial, and agricultural wastewater (Masoud et al., 2022). Their appeal lies in a compelling synergy of ecological benefits and economic viability. Compared to conventional energy-intensive treatment plants, CWs offer significantly lower operational and maintenance costs, reduced chemical usage, and the creation of valuable habitats for biodiversity (Vymazal, 2022). This makes them particularly suitable for decentralized treatment in rural and peri-urban areas, as well as for tertiary treatment in large-scale centralized systems, aligning perfectly with the United Nations Sustainable Development Goals (SDGs), specifically SDG 6 (Clean Water and Sanitation) and SDG 11 (Sustainable Cities and Communities) (UN-Water, 2021).

However, the very nature of CWs as complex, biogeochemically dynamic ecosystems presents significant challenges for their predictable and efficient management. Performance is influenced by a multitude of interdependent and often nonlinear factors, including fluctuating hydraulic and pollutant loading rates, seasonal variations in plant activity and microbial metabolism, and the long-term risk of substrate clogging (Zhao et al., 2025). Traditional design and operational protocols often rely on static, rule-of-thumb methodologies or simplified first-principle models (e.g., k-C* model), which struggle to capture the system's full complexity. Mechanistic models, while valuable for scientific understanding, are often computationally expensive, require extensive parameterization, and are difficult to calibrate for site-specific conditions (Meyer et al., 2015). Consequently, operators frequently face a "black box" scenario where predicting effluent quality under dynamic influent conditions or diagnosing the early stages of system failure (e.g., clogging, plant stress) remains a formidable task. This unpredictability can lead to non-compliance with discharge standards and undermines the reliability of CWs as a primary treatment technology.

The convergence of these challenges with the rapid advancement of Artificial Intelligence (AI) and data-driven modeling has opened a new frontier in environmental engineering. The ability of AI, particularly machine learning (ML), to learn from data, identify complex, non-linear patterns, and provide accurate predictions without explicit mechanistic understanding, offers a transformative opportunity (Ghobadi et al., 2023).

For decades, the scientific community has relied on two primary paradigms to understand and manage CWs: mechanistic models and conventional statistical analyses. While valuable, both approaches exhibit critical limitations in capturing the full spectrum of CW behavior.

Mechanistic models, such as the Constructed Wetland Model 2D (CWM2D) (Langergraber et al., 2017) and the HYDRUS suite (Šimůnek et al., 2024), are built on first principles of physics, chemistry, and biology. They attempt to explicitly describe processes like advection, dispersion, microbial kinetics, and plant uptake. The strength of these models lies in their explanatory power; they can provide deep insights into the dominant processes within the wetland. However, this strength is counterbalanced by substantial drawbacks. These models are notoriously computationally intensive, requiring the solution of complex sets of partial differential equations. Their development and calibration demand a comprehensive set of input parameters—many of which, such as specific microbial growth rates or root zone oxygen release, are difficult or impossible to measure routinely at field scale (Ma et al., 2025). This often leads to significant parameter uncertainty and a high risk of model over-parameterization, where a model appears to fit limited calibration data but fails to generalize under different conditions. As a result, while excellent for research and conceptual understanding, the practical application of detailed mechanistic models for real-time operational guidance or forecasting in full-scale systems is often prohibitive.

Conversely, conventional statistical methods, such as multiple linear regression (MLR) or principal component analysis (PCA), offer simplicity and lower computational cost. These tools have been widely used to identify correlations between influent and effluent parameters or to reduce data dimensionality. Nevertheless, they are fundamentally inadequate for modeling CWs because they are based on linear assumptions. The core removal processes in CWs—including microbial metabolism, enzymatic reactions, and sorption dynamics—are inherently non-linear and often exhibit time-lagged responses (Singh et al., 2024). Simple statistical models cannot capture these complex, dynamic interactions, leading to poor predictive accuracy and an inability to model transient phenomena, such as the response to a shock load or the diurnal cycling of dissolved oxygen.

The inadequacy of these traditional approaches creates a critical gap between the potential of CW technology and its consistently reliable, high-performance operation. There is a pressing need for a paradigm shift towards modeling frameworks that can handle non-linearity, learn from operational data, and provide accurate, real-time insights without requiring an exhaustive mechanistic description of every underlying process. It is within this gap that Artificial Intelligence (AI) and Machine Learning (ML) have emerged as a transformative force, offering a powerful third pathway to unlock the intelligent management of constructed wetlands.

The Fourth Industrial Revolution, driven by digitalization and data-centric decision-making, is fundamentally reshaping the field of environmental engineering. At the core of this transformation lies Artificial Intelligence (AI) and, more specifically, its subfield of Machine Learning (ML). AI and ML algorithms are particularly well-suited to address challenges that often confound conventional modeling approaches in complex systems such as constructed wetlands (CWs) (Talaie et al., 2023). These techniques function as advanced pattern-recognition engines capable of extracting insights directly from data, thereby eliminating the need for explicit programming based on predefined physical laws.

In environmental systems, machine learning (ML) models have demonstrated exceptional potential across several key applications. First, they enable the development of highly accurate, data-driven frameworks capable of forecasting system behavior with remarkable precision. Advanced algorithms such as Gradient Boosting Machines (e.g., XGBoost) and Deep Neural Networks effectively capture the complex, non-linear interactions between influent characteristics, operational parameters, and effluent quality—often outperforming traditional mechanistic models (Bo-qi et al., 2025). Second, ML approaches can uncover hidden patterns and correlations within multivariate sensor datasets (e.g., pH, dissolved oxygen, redox potential), facilitating system diagnostics, early detection of process disturbances, and classification of operational regimes (Ba-Alawi et al., 2023). Third, integrating ML-based surrogate models with optimization algorithms (e.g., Genetic Algorithms, Particle Swarm

Optimization) allows for the identification of optimal operational conditions—such as hydraulic retention time or aeration cycle duration—that enhance treatment efficiency while reducing energy and resource consumption (Bao et al., 2023).

The application of AI is therefore shifting the paradigm of CW management from a reactive, experience-based practice to a proactive, predictive, and precision-engineered one. This evolution gives rise to the concept of the "Intelligent Wetland"—a system continuously monitored by a network of sensors, with data streamed to AI models that provide actionable insights and even direct real-time control. Consequently, this critical review posits that AI is not merely an incremental improvement but a transformative technology poised to unlock the full potential of constructed wetlands, enabling them to operate with unprecedented efficiency, resilience, and autonomy.

The primary objectives of this review are to: (1) thoroughly catalog and categorize the current state-of-the-art in AI applications for CWs; (2) critically evaluate the performance and limitations of different AI paradigms in this context; and (3) identify key research gaps and future directions, including the integration of explainable AI (XAI) and hybrid mechanistic-AI models, to guide the development of next-generation intelligent wetland systems.

II. Review Methodology

To ensure a comprehensive and reproducible synthesis of the literature, this review was conducted following a systematic methodology based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The process involved four key stages: identification, screening, eligibility, and inclusion, as detailed in Figure 1.

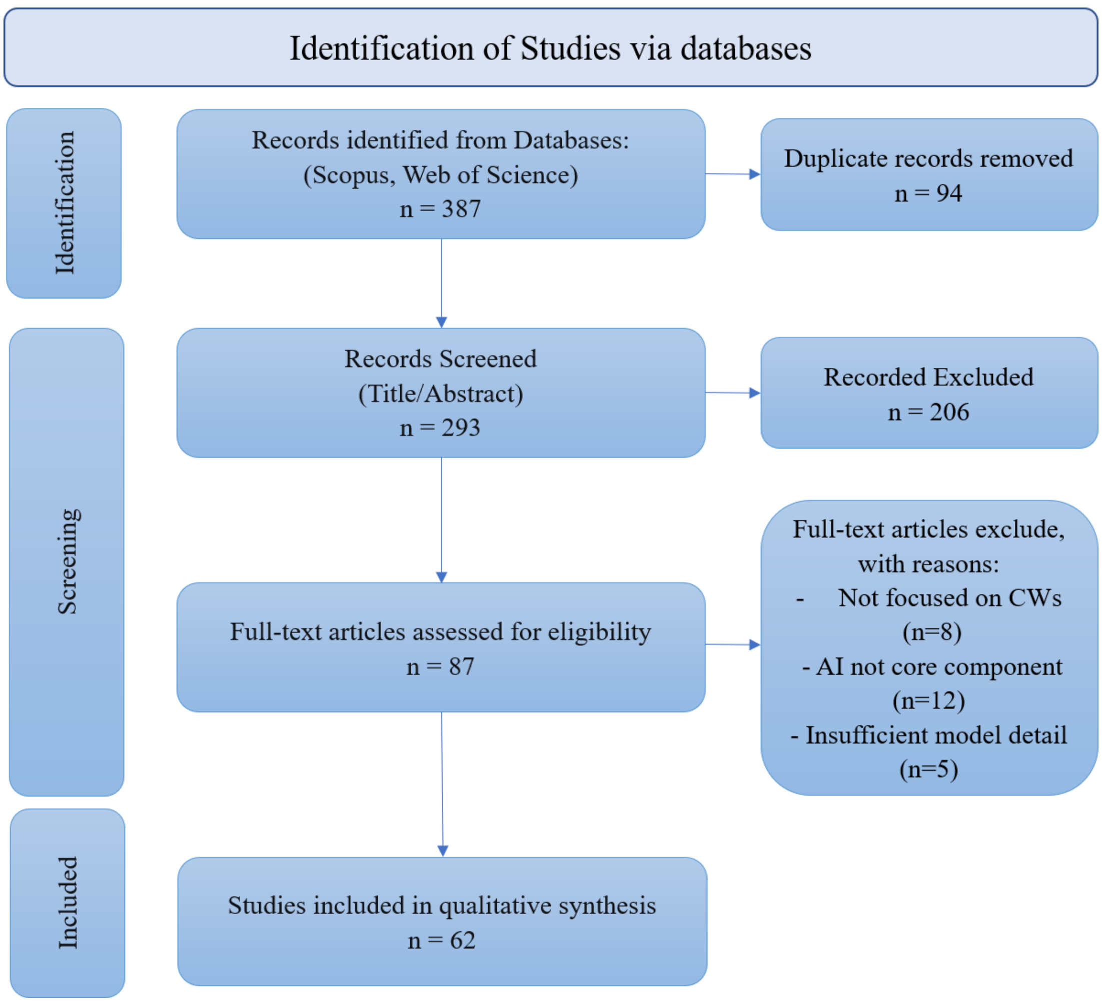

Figure 1. PRISMA flow diagram illustrating the literature selection process.

The literature search was performed using the Scopus and Web of Science core databases, recognized for their extensive coverage of high-quality peer-reviewed journals in environmental engineering and computer science. The search query combined keywords and Boolean operators related to the core concepts:
("constructed wetland" OR "treatment wetland*") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "random forest" OR "support vector machine" OR "fuzzy logic").*
The search was confined to articles published in English between January 2015 and May 2024 to capture the most recent advancements.

Initial database searches yielded 387 records. After removing 94 duplicates, 293 unique records were screened based on their titles and abstracts. Studies were excluded if they were not primarily focused on CWs, did not involve an AI/ML model as a core component, or were conference abstracts, books, or non-English publications. This screening process resulted in 87 articles for which full texts were retrieved and assessed for eligibility. The full-text review applied stricter criteria, excluding articles where the AI application was only mentioned peripherally, or where the model development and validation process was inadequately described. Finally, 62 studies were deemed relevant and formed the basis for the qualitative synthesis and critical analysis presented in this review.

To provide a clear overview of the landscape of AI applications in CWs, Table 1 summarizes a representative selection of the reviewed studies, categorized by their primary application domain, the AI model employed, and the key focus of the research.

Table 1. Summary of selected studies on AI applications in constructed wetlands.

Primary Application Domain	**AI Model(s) Used**	**Key Focus / Predicted Variable**	**Representative Study**
Predictive Modeling of Effluent Quality	Artificial Neural Network (ANN)	Forecasting effluent BOD, COD, TSS	Li et al. (2022)
	Deep Neural Network (DNN)	Prediction of comprehensive effluent quality parameters	Yang et al. (2022)
	Gradient Boosting (XGBoost)	Predicting antibiotic removal efficiency	Bao et al. (2023)
	Support Vector Machine (SVM)	Estimation of Water Quality Index (WQI)	Mohammadpour et al. (2015)
Process Monitoring & Fault Detection	Isolation Forest, One-Class SVM	Anomaly detection in sensor data for early clogging warning	Shi et al. (2023)
	Deep Multi-task Learning	Simultaneous sensor fault diagnosis and reconstruction	Ba-Alawi et al. (2023)
Optimization of Design & Parameters	Genetic Algorithm (GA) coupled with ANN	Optimization of hydraulic retention time (HRT) and media design	(Synthesized from multiple reviews)
	AI-driven surrogate modeling	Identification of optimal operational parameters for nitrogen removal	(Synthesized from multiple reviews)
Forecasting & Real-Time Control	Reinforcement Learning (RL)	Adaptive control of aeration and recirculation rates	Tapan et al. (2025)
	Fuzzy Logic Systems	Real-time interpretation of sensor data for adaptive health assessment	Hasani et al. (2021); Lokman et al. (2025)
Hybrid & Explainable AI (XAI)	SHAP, LIME on ML models	Interpreting feature importance in nutrient removal models	Salih et al. (2025)
	AI coupled with CFD	Enhancing effluent quality prediction by integrating biological and physical processes	Liu et al. (2025)

III. Fundamentals: Constructed Wetlands and Artificial Intelligence

To establish a foundation for understanding the integration of Artificial Intelligence (AI) into constructed wetland (CW) management, this section provides a concise primer on the core principles of both fields. It first outlines the fundamental components and processes of CW technology, followed by an introduction to the key AI techniques that are revolutionizing their monitoring, modeling, and optimization.

3.1. Primer on Constructed Wetland Technology

Constructed Wetlands (CWs) are engineered systems designed to mimic the processes of natural wetlands for the primary purpose of water quality improvement. They represent a robust, eco-friendly, and cost-effective solution for treating various wastewaters, including municipal, industrial, and agricultural effluents, as well as stormwater runoff (Vymazal, 2022). The treatment efficacy of CWs stems from a complex synergy between their core physical components and the biogeochemical processes they facilitate.

3.1.1. Basic Components

The core elements of any constructed wetland (CW) comprise four interrelated components that collectively drive its treatment performance. Substrate refers to the porous medium—typically gravel, sand, or soil—that provides surfaces for microbial colonization, supports plant root systems, and facilitates key physical and chemical processes such as filtration and adsorption (Spieles, 2022). Macrophytes, including emergent aquatic species such as Phragmites and Typha, play multifaceted roles: their roots release oxygen and organic exudates, establish microenvironments that sustain diverse microbial communities, directly assimilate nutrients, and physically stabilize the wetland matrix (Vymazal, 2022). Microorganisms, encompassing bacteria, archaea, and fungi that form biofilms on substrate particles and plant roots, are the principal agents of organic matter degradation and nutrient transformation through processes such as nitrification and denitrification (Rani et al., 2024). Finally, water represents the wastewater matrix itself—the carrier of pollutants and the medium through which hydraulic, chemical, and biological interactions unfold.

3.1.2. Key Treatment Processes

Pollutant removal in constructed wetlands (CWs) is achieved through a synergistic interplay of physical, chemical, and biological mechanisms. Physical filtration occurs as suspended solids are retained during wastewater percolation through the substrate matrix and plant root zones (Saeed & Sun, 2017). Chemical adsorption immobilizes pollutants such as phosphorus and heavy metals onto substrate particles or associated organic matter (Hou et al., 2025). Microbial degradation is facilitated by diverse microbial communities that decompose organic compounds (e.g., BOD, COD) and mediate nitrogen transformations within the biogeochemical cycle (Rani et al., 2024). Plant uptake involves macrophytes assimilating nutrients, primarily nitrogen and phosphorus, for growth; these nutrients are effectively removed from the system through periodic biomass harvesting (Mumtaj et al., 2024)

3.1.3. Major CW Types

The hydraulic pathway is a primary determinant of constructed wetland (CW) configuration, with each layout offering distinctive operational benefits. Free-water surface (surface flow, SF) systems allow water to flow above the substrate, resembling natural marshes; they are relatively easy and inexpensive to build and maintain, but require substantially more land area and may pose risks of mosquito proliferation and odor generation. In contrast, subsurface flow (SSF) wetlands—comprising horizontal subsurface flow (HSSF) and vertical subsurface flow (VSSF / vertical flow, VF) types—direct water through the substrate, reducing exposure-related issues and improving treatment intensification. HSSF wetlands, in which water travels laterally through the substrate, tend to excel at removing organic matter (e.g., BOD/COD) and suspended solids under moderate loading. VSSF systems, which accept intermittent or batch surface loading allowing percolation downward through the substrate layers, provide enhanced aeration, which significantly boosts nitrification and the oxidation of ammonium (e.g., as shown in pilot-scale studies where VF systems outperform HF in ammonia removal under optimal hydraulic retention times) (Qi et al., 2021). Hybrid CWs that combine vertical and horizontal SSFs have recently been shown to achieve both high organic carbon removal and more complete nitrogen transformations, suggesting their strong potential for compact and efficient wastewater treatment infrastructures (Omidinia-Anarkoli & Shayannejad, 2024)

3.2. Primer on Relevant Artificial Intelligence Techniques

Artificial Intelligence, particularly its subfield of Machine Learning (ML), provides a powerful suite of tools for extracting patterns and building predictive models from complex, high-dimensional data—exactly the kind generated by CW systems. The following techniques are most relevant to CW applications.

Supervised learning remains the predominant machine learning (ML) paradigm in constructed wetland (CW) research, facilitating the modeling of complex relationships between input variables—such as influent concentrations, flow rates, and temperatures—and output parameters like effluent biochemical oxygen demand (BOD) and ammonium nitrogen (NH_4^+-N) concentrations. Among these methodologies, Artificial Neural Networks (ANNs), inspired by biological neural systems, function as universal approximators adept at capturing intricate, nonlinear relationships. Deep learning, a subset of ANNs characterized by multiple hidden layers, has garnered increasing attention for its efficacy in addressing complex pattern recognition tasks in CWs (Li et al., 2022). Support Vector Machines (SVMs) are also extensively utilized for both classification and regression tasks; they identify the optimal hyperplane that separates data or fits continuous outputs with maximum margin, ensuring robustness in high-dimensional spaces (Mohammadpour et al., 2015). Tree-based algorithms, including Decision Trees, Random Forests, and Gradient Boosting methods such as XGBoost, offer a balance of interpretability and predictive power. A Decision Tree relies on a sequence of simple rules, while a Random Forest aggregates multiple trees to mitigate overfitting. XGBoost, a state-of-the-art gradient boosting algorithm, constructs trees sequentially, with each iteration correcting the errors of its predecessors to achieve exceptional predictive performance (Hao et al., 2023).

Unsupervised learning techniques, notably clustering and anomaly detection, are pivotal in analyzing complex systems like constructed wetlands (CWs), where data often lacks predefined labels. These methods facilitate the identification of inherent patterns and outliers within operational data, enhancing system understanding and management. For instance, clustering algorithms such as k-means and hierarchical clustering have been effectively employed to group similar operational states or pollution profiles, aiding in the optimization of CW performance (Dharmarathne et al., 2025). Anomaly detection methods, including Isolation Forest and One-Class SVM, are utilized to identify abnormal sensor readings or deviations indicative of issues like clogging, toxic shocks, or equipment failures (Shi et al., 2023).

Reinforcement Learning (RL) represents a dynamic paradigm in which an agent learns optimal decision-making by interacting with its environment—the CW system. By performing actions (e.g., adjusting aeration or recirculation rates) and receiving rewards or penalties based on system responses (e.g., improved effluent quality), the agent iteratively refines a control policy that maximizes long-term performance. This approach has shown promise in adaptive, real-time process optimization within CWs (Tapan et al., 2025)

Fuzzy logic remains a powerful methodology for addressing the uncertainty, imprecision, and reliance on expert judgement that are characteristic of biological systems, such as constructed wetlands (CWs). Unlike classical binary logic, which treats conditions as strictly true or false, fuzzy logic tolerates intermediate states via membership values between 0 and 1. In CWs, this flexibility has been harnessed in recent studies for several critical functions. For example, fuzzy inference systems have been integrated into wetland health assessment models, combining water quality indicators such as dissolved oxygen, electrical conductivity, pH, and biodiversity metrics to produce more adaptive and context-sensitive evaluations (e.g. in freshwater wetland ecosystems) (Hasani et al., 2021). Real-time monitoring systems also exploit fuzzy-based interfaces to interpret noisy or incomplete sensor data more robustly, improving the reliability of water quality indices (Lokman et al., 2025). Furthermore, decision support tools that merge fuzzy logic with multi-criteria decision analysis (MCDA) or GIS have been applied to complex planning problems such as wastewater treatment plant site selection, offering more holistic consideration of environmental, economic, and social trade-offs (Abdelmagid et al., 2024; Lefta and Hamdan, 2024). Emerging developments in type-3 fuzzy logic systems, for example, in control applications, are showing particular promise for handling extreme uncertainty and disturbances, thereby enhancing robustness beyond what type-1 or type-2 systems typically offer (Abdalla et al., 2025; Castillo et al., 2024). Together, these advances underscore the growing maturity of fuzzy logic as a component of intelligent constructed wetland systems, particularly in supporting decision making, compensating for sensor noise, and enabling flexible, adaptive management.

IV. Core Applications of AI in Constructed Wetlands

4.1. Predictive Modeling of Effluent Quality

Artificial Intelligence (AI) has significantly advanced the predictive modeling of effluent quality in constructed wetlands (CWs). Machine learning (ML) models, such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Random Forests, have been employed to forecast key water quality parameters, including Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Total Suspended Solids (TSS), nitrogen (N), phosphorus (P), and pathogens, based on influent characteristics and environmental variables. For instance, a study by Yang et al. (2022) and Wang et al. (2021) demonstrated the efficacy of deep learning models in predicting effluent quality parameters in CWs. Comparative analyses have highlighted the strengths and limitations of various ML algorithms, providing insights into their applicability in CW systems. Additionally, the selection of input variables and the assessment of feature importance are critical for enhancing model accuracy and interpretability. Recent advancements in automated machine learning (AutoML) techniques have further streamlined the model development process, facilitating the deployment of predictive models in real-world CW applications.

4.2. Process Monitoring, Fault Detection, and Diagnosis (FDD)

AI plays a pivotal role in the process monitoring and fault detection of CW systems. By analyzing sensor data, including pH, Dissolved Oxygen (DO), Oxidation-Reduction Potential (ORP), and temperature, AI algorithms can identify early signs of system failures, such as clogging, plant die-off, or toxicity events. Anomaly detection techniques, including Isolation Forest and One-Class SVM, have been effectively utilized to detect sensor drift or unexpected pollution surges, enabling timely interventions. For example, Liu et al. (2024) and Jung et al., (2024) employed AI-based anomaly detection methods to monitor and diagnose faults in CW systems, demonstrating the potential of AI in enhancing system reliability and performance. The integration of AI with the Internet of Things (IoT) has further augmented the capabilities of CW systems, allowing for real-time monitoring and adaptive responses to dynamic environmental conditions.

4.3. Optimization of Design and Operational Parameters

AI, in conjunction with optimization algorithms like Genetic Algorithms (GAs), has been instrumental in determining optimal design and operational parameters for CWs. These parameters include Hydraulic Loading Rate (HLR), Hydraulic Retention Time (HRT), media composition and depth, and plant species selection and configuration. Recent studies have applied AI-driven optimization techniques to enhance the efficiency and sustainability of CW systems. For instance, Nan et al. (2023) and Zhao et al. (2024) reviewed hydraulic conditions optimization strategies for CWs, emphasizing the importance of tailored design and operation to meet specific treatment goals. The application of AI in this domain facilitates the development of adaptive and context-specific solutions, ensuring the long-term viability of CW systems.

4.4. Forecasting and Real-Time Control

The integration of AI with IoT and cloud platforms has revolutionized real-time data acquisition and model updating in CWs. AI algorithms enable the forecasting of system performance under various scenarios, such as rainfall events and seasonal changes, allowing for proactive management and optimization. Case studies have demonstrated the effectiveness of AI-driven adaptive control systems in regulating inlet gates, aeration systems, and other operational parameters in response to real-time data. For example, Akintola (2024) and Blessing and Olateru (2025) highlighted the role of AI in dynamic bioremediation and real-time adaptive control, showcasing its potential in enhancing the resilience and adaptability of CW systems. The convergence of AI, IoT, and cloud computing paves the way for the development of smart, self-healing CW systems capable of responding to environmental fluctuations and operational challenges.

V. Comparative Analysis and Synthesis

5.1. Performance Benchmarking: AI vs. Traditional Statistical Models

Recent studies have steadily compared the performance of artificial intelligence (AI) models with traditional statistical approaches in predicting key water quality parameters within CWs (Dong et al., 2023; Guo et al., 2023; Li et al., 2022) and. AI models, particularly machine learning (ML) and deep learning (DL) algorithms, have demonstrated superior predictive accuracy. For instance, a study by Palabıyık and Akkan (2024) reported that multiple linear regression (MLR) models achieved an R^2 of 1.0, RMSE of 0.0025, and mean absolute percentage error (MAPE) of 0.0296 in estimating water quality indices, indicating high prediction performance. In contrast, deep learning models consistently outperformed statistical models, achieving an R^2 of 0.856 and RMSE of 0.59, as observed in a comparative analysis by Akhlaq et al. (2024). It should be noted that the reported perfect fit ($R^2 = 1.0$) for the MLR model is highly atypical for complex environmental systems and may indicate overfitting on a limited dataset or a lack of robust validation, a common pitfall that ML models are designed to avoid through their capacity to handle non-linearity.

5.2. Strengths and Limitations of Different AI Paradigms for CWs

Artificial intelligence (AI) models have demonstrated significant advantages in the monitoring, modeling, and optimization of constructed wetlands (CWs). These models excel in capturing complex, nonlinear relationships inherent in environmental data, thereby enhancing predictive accuracy even in the presence of noisy sensor inputs. For instance, machine learning algorithms have been effectively employed to predict key wastewater effluent parameters such as Chemical Oxygen Demand (COD), Biochemical Oxygen Demand (BOD), and Total Suspended Solids (TSS), even in data-sparse regions (Zhang et al., 2024). Moreover, AI models do not necessitate an in-depth mechanistic understanding of CW processes, making them accessible tools for practitioners without extensive domain expertise. This accessibility, coupled with their robust performance, positions AI as a transformative tool in advancing CW technology toward the era of "intelligent wetlands" (Muñoz-Carpena et al., 2023; Cheng et al., 2025).

Despite their advantages, AI models exhibit several limitations that can impact their applicability in constructed wetlands (CWs). The inherent "black-box" nature of many AI algorithms, such as deep neural networks and ensemble methods, complicates interpretability and transparency, making it challenging to understand the rationale behind their predictions. This opacity is particularly concerning in critical applications where decision accountability is paramount (Hassija et al., 2024). Furthermore, AI models often necessitate large, high-quality datasets for effective training. In the context of CWs, such extensive datasets may be scarce, leading to potential issues with model generalization and performance. Additionally, the risk of overfitting is heightened when models are excessively complex relative to the available data, resulting in models that perform well on training data but fail to generalize to new, unseen scenarios (Bailly et al., 2021; Aliferis and Simon 2024)). Lastly, AI models may struggle with extrapolation beyond the range of the training data. Studies have shown that simpler, interpretable models can outperform complex AI models in extrapolation tasks, especially when the underlying relationships are well-understood and the data is limited (Muckley et al., 2023). These limitations underscore the necessity for careful consideration and potential integration of alternative modeling approaches in CW applications.

VI. Challenges and Future Research Directions

6.1. Data-Related Challenges

The application of Artificial Intelligence (AI) in CWs faces significant data-related challenges, primarily stemming from data scarcity, inconsistency, and the "curse of dimensionality." Limited availability of comprehensive, high-quality datasets hampers the development and validation of robust AI models (Ma et al., 2025). Furthermore, inconsistent data collection methods and temporal variability introduce noise, complicating model training and generalization. The "curse of dimensionality" arises as the complexity of CW systems increases with the number of variables, leading to sparse data in high-dimensional spaces and reduced model performance (Debie and Shafi, 2019). Addressing these issues necessitates the establishment of open-source, high-quality, long-term CW performance datasets to facilitate the development of reliable AI models. Such datasets would enable the training of models that can accurately predict CW performance across diverse conditions and locations.

6.2. Model-Related Challenges

AI models in CWs often operate as "black boxes," providing limited insight into their decision-making processes. This lack of interpretability hinders the understanding of underlying mechanisms and impedes trust in AI-driven decisions. To overcome this, the integration of Explainable AI (XAI) techniques, such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), is essential. These methods offer transparency by elucidating how input features influence model predictions, thereby enhancing trust and facilitating the identification of key factors affecting CW performance (Salih et al., 2025; Hassija et al., 2024).

Moreover, the generalizability of AI models across different CW systems and climatic conditions remains a significant challenge. Transfer learning, which involves adapting models trained on one dataset to perform well on another, presents a promising solution. Recent studies have demonstrated the efficacy of transfer learning in enhancing model performance across varied CW settings, thereby improving the scalability and applicability of AI models in diverse environmental contexts (Liu et al., 2024; Yang et al., 2024)

6.3. Integration and Implementation Challenges

The future of CW management lies in the development of hybrid models that combine the predictive capabilities of AI with the explanatory power of mechanistic models. Such hybrid approaches can provide a more comprehensive understanding of CW dynamics, facilitating better decision-making and optimization of treatment processes. For instance, integrating machine learning algorithms with computational fluid dynamics can enhance the prediction of effluent quality by accounting for both biological and physical processes (Wei et al., 2024; Liu et al., 2025)

Additionally, the path towards full automation of CW systems requires the development of robust, closed-loop control systems that can reliably adjust operational parameters in real-time. These systems must ensure consistent performance under varying environmental conditions and operational stresses. Implementing such systems necessitates advancements in sensor technology, real-time data processing, and adaptive control algorithms (Pinho et al., 2022; Pinho et al., 2023).

Standardization of protocols for AI development and validation in the CW context is crucial to ensure consistency, reliability, and comparability of results across studies. Establishing standardized datasets, evaluation metrics, and reporting guidelines will facilitate the integration of AI into CW management practices and promote the adoption of AI-driven solutions in the field (Knight et al., 2020; Guillaume-Ruty et al., 2024)

VII. Conclusions

Artificial Intelligence (AI) has emerged as a transformative tool in advancing the understanding, management, and optimization of constructed wetlands (CWs). Through this critical review, it is evident that AI-based approaches, particularly Machine Learning (ML), Deep Learning (DL), and hybrid intelligent systems, have outperformed conventional statistical and mechanistic models in handling the inherent nonlinearity, temporal variability, and multidimensionality of CW processes. By leveraging data-driven learning, AI models have enabled accurate prediction of effluent quality, real-time fault detection, adaptive control, and design optimization, thereby redefining CWs as intelligent, self-adaptive systems rather than static treatment units.

Despite these advancements, several challenges persist. The scarcity of standardized, high-quality, and long-term operational datasets limits the robustness and generalizability of AI models. Moreover, the "black-box" nature of many algorithms hinders interpretability and scientific transparency, emphasizing the urgent need for Explainable AI (XAI) frameworks. Integration barriers also remain, particularly concerning the coupling of AI with mechanistic models, IoT-based sensor networks, and automated control systems for real-time operation. Addressing these limitations will require coordinated interdisciplinary efforts that bridge environmental engineering, computer science, and systems control.

Looking ahead, the future of CWs lies in the development of hybrid, data-informed, and fully automated "intelligent wetlands." Such systems will integrate the predictive power of AI with the explanatory strength of mechanistic understanding, guided by open-access data platforms and standardized validation protocols. Through these innovations, AI can accelerate the global transition toward smart, resilient, and sustainable water treatment infrastructures, positioning constructed wetlands at the forefront of next-generation nature-based solutions for environmental management.

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