

“Nature-Based Solutions Optimization Using AI and Machine Learning for Sustainable Urban Water Management”

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Abstract: Rapid urbanization, industrialization, and climate change are placing significant pressure on urban water resources, resulting in increased flooding, pollution, and water scarcity, while conventional gray infrastructure systems often lack adaptability and long-term sustainability. This study aims to optimize Nature-Based Solutions (NBS) such as green roofs, bioswales, constructed wetlands, rain gardens, and urban green spaces for sustainable urban water management by leveraging Artificial Intelligence (AI) and Machine Learning (ML) techniques to enhance system efficiency, adaptability, and resilience. Multi-source datasets including hydrological parameters (rainfall, runoff, infiltration), water quality indicators (BOD, COD, TSS, nutrients), land-use/land-cover data, soil characteristics, and climate projections are utilized, followed by preprocessing techniques such as normalization and feature selection. Supervised learning models (e.g., Random Forest, Support Vector Machine, Artificial Neural Networks) are applied for performance prediction, while clustering methods and GIS-based spatial analysis identify suitability zones; optimization algorithms such as Genetic Algorithms and Particle Swarm Optimization are integrated to determine optimal design and placement of NBS components. A real-time IoT-based monitoring framework is proposed to enable adaptive model updating and predictive analysis. The expected outcomes include improved runoff reduction, enhanced pollutant removal efficiency, minimized lifecycle costs, and data-driven decision support for urban planners and policymakers, ultimately promoting resilient, cost-effective, and environmentally sustainable urban water management systems.

Keywords: Nature-Based Solutions (NBS), Artificial Intelligence (AI), Machine Learning (ML), Sustainable Urban Water Management, Stormwater Management, Hydrological Modeling, Predictive Analytics, Optimization Algorithms,

Introduction

Urban water systems are increasingly stressed by rapid urbanization, climate variability, and infrastructure aging, resulting in frequent flooding, declining water quality, and resource inefficiencies. Traditional gray infrastructure approaches are often insufficient to address these multidimensional challenges, particularly under changing precipitation patterns and extreme weather events [Ahmad Ferdowsi et al., 2024]. Sustainable and integrated water management frameworks have therefore been emphasized to enhance resilience, decarbonization, and long-term adaptability of urban systems [Xinyu Pan et al., 2025]. At the

same time, integrated water resources management and indicator-based assessment models have highlighted the need for holistic planning that incorporates environmental, social, and economic dimensions [Mohamed Ben-Daoud et al., 2021]. Nature-Based Solutions (NBS) have emerged as a promising alternative by utilizing ecosystem processes to manage stormwater, improve water quality, and enhance urban resilience. Conceptual clarifications define NBS as nature-inspired interventions that address societal challenges while providing co-benefits such as biodiversity enhancement and climate regulation [Barbara Sowińska-Świerkosz et al., 2022]. Reviews on urban green and blue infrastructure demonstrate their effectiveness in mitigating flood risks, enhancing

ecosystem services, and improving urban livability under climate change scenarios [Kornelia Przestrzelska et al., 2024; Yunong Yao et al., 2025]. Furthermore, optimization-based planning of NBS at catchment scales has shown the importance of spatial prioritization and trade-off analysis to maximize hydrological and economic benefits [Leyang Liu et al., 2023]. However, implementation challenges remain due to data uncertainty, methodological inconsistencies, and limited long-term monitoring [Gemechis B. Mosisa et al., 2025].

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into water management offers transformative potential to address these limitations through predictive modeling, real-time monitoring, and adaptive optimization. Recent reviews emphasize the growing role of deep learning, hybrid models, and data-driven approaches in urban water demand forecasting, flood prediction, and infrastructure monitoring [Guangtao Fu et al., 2022; Ashraf A. Ahmed et al., 2024]. AI-driven frameworks have demonstrated significant improvements in water quality prediction accuracy and operational efficiency in treatment and distribution systems [Mahmoud Y. Shams et al., 2024; Yu-Qi Wang et al., 2025]. Additionally, IoT-integrated ML systems enable real-time water quality monitoring and decision-making, particularly in resource-constrained regions [Samson Otieno Ooko et al., 2025]. Optimization algorithms such as genetic algorithms and reinforcement learning have further enhanced system-level performance and sustainability outcomes [Abdulrazzaq Shaamala et al., 2024; Maddalena Zuccotto et al., 2024].

Despite these advancements, a significant research gap exists in integrating AI/ML-driven optimization directly with Nature-Based Solutions for urban water systems. While studies have explored AI in environmental management broadly [Zhuling Guo et al., 2025] and the application of AI in NBS planning from human and ecological perspectives [Veljko Prodanovic et al., 2024], a comprehensive framework combining predictive analytics, spatial suitability analysis, real-time monitoring, and multi-objective optimization for NBS remains limited. Therefore, this study proposes an integrated AI- and ML-based optimization framework to enhance the efficiency, adaptability, and long-term resilience of Nature-Based Solutions in sustainable urban water management, supporting data-driven planning and climate-resilient urban development.

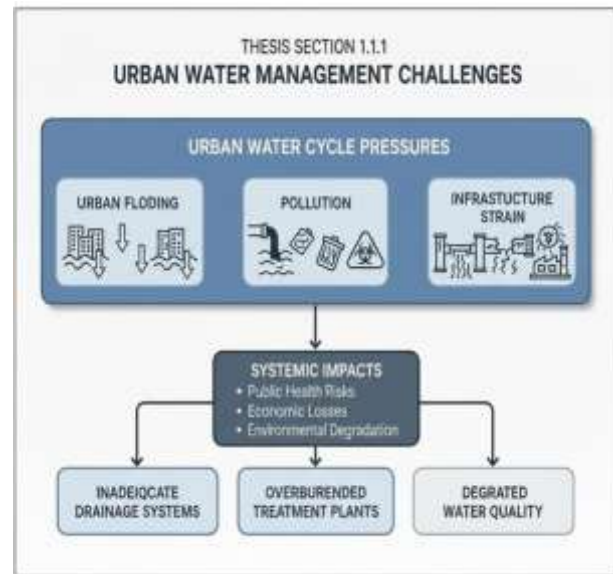


Figure1.1: Urban Water Management Challenges

Urban stormwater management has undergone a paradigm shift from centralized drainage systems toward decentralized and smart approaches that enhance flexibility and sustainability. Smart stormwater frameworks integrating sensors, data platforms, and automated control have demonstrated improved peak flow reduction and adaptive basin operation under extreme rainfall events [James L. Webber et al., 2022; Shadab Shishegar et al., 2021]. However, most smart water management applications prioritize hydraulic efficiency rather than ecological multifunctionality, creating a gap between digital innovation and ecosystem-based strategies. Bridging this gap requires coupling smart monitoring systems with Nature-Based Solutions (NBS) to ensure both hydrological control and environmental co-benefits.

Recent advances in artificial intelligence further strengthen the feasibility of such integration. Deep learning and hybrid machine learning models have significantly improved urban flood forecasting, leakage detection, and contamination prediction, outperforming traditional statistical techniques [Guangtao Fu et al., 2022; Ashraf A. Ahmed et al., 2024]. Explainable Artificial Intelligence (XAI) approaches, including SHAP and LIME methods, have enhanced transparency and stakeholder trust in urban water decision-making, improving runoff prediction accuracy and energy efficiency in operational systems [Shofia Saghya Infant et al., 2025]. These developments highlight the importance of interpretable and robust AI frameworks when applied to public infrastructure and sustainability planning. Water quality monitoring and prediction have also benefited from AI-driven methodologies. Ensemble learning, gradient boosting, artificial neural networks, and graph neural networks have achieved high predictive accuracy for Water Quality Index (WQI) estimation, even under sparse monitoring conditions [Mahmoud Y. Shams et al., 2024; Zilin Li et al., 2024]. Comparative assessments demonstrate that optimized ANN and boosting algorithms can achieve R^2 values above 0.95, reinforcing the reliability of ML-based predictive tools in urban water systems [Mosaraf Hosan Nishat et al., 2025; Nida Nasir et al., 2022]. These advancements provide a strong technical foundation for integrating predictive water quality modeling into NBS performance assessment and optimization.

From an optimization perspective, metaheuristic algorithms

and AI-driven green infrastructure planning models have shown strong potential for multi-objective environmental management problems. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and reinforcement learning approaches enable simultaneous consideration of hydrological performance, economic cost, and environmental benefits [Abdulrazzaq Shaamala et al., 2024; Maddalena Zuccotto et al., 2024]. Reviews on metaheuristic taxonomy further emphasize their suitability for complex, nonlinear environmental systems with multiple constraints [Kanchan Rajwar et al., 2023]. These techniques are particularly relevant for determining optimal placement, sizing, and configuration of NBS under varying climatic and urban growth scenarios. Moreover, the global discourse on sustainable and green artificial intelligence underscores the necessity of aligning AI deployment with environmental goals. Green AI frameworks advocate for energy-efficient model development and carbon-conscious computation to ensure that technological advancements themselves remain sustainable [Verónica Bolón-Canedo et al., 2024; Raghu Raman et al., 2024]. Integrating such principles into urban water optimization ensures that AI-enhanced NBS frameworks contribute positively to climate mitigation and Sustainable Development Goals (SDGs).

Despite the substantial body of research on AI in water resources and the expanding literature on Nature-Based Solutions, limited studies have developed a unified, data-driven decision-support system that simultaneously incorporates predictive modeling, spatial analysis, optimization algorithms, and real-time IoT monitoring for NBS performance enhancement. Existing frameworks often address isolated components such as water quality prediction, flood forecasting, or biodiversity planning [Veljko Prodanovic et al., 2024; Gemechis B. Mosisa et al., 2025]. Therefore, there is a clear need for an integrated AI-ML optimization framework tailored specifically to enhance the efficiency, adaptability, and long-term resilience of NBS in urban water management. This research aims to fill that gap by proposing a comprehensive, scalable, and climate-resilient approach that supports evidence-based planning, operational intelligence, and sustainable urban transformation.

Background of the Study Urban water systems worldwide are facing unprecedented stress due to rapid population growth, expanding infrastructure demands, and environmental degradation. Increasing water consumption, pollution loads, and aging drainage networks have reduced the efficiency and reliability of traditional water management systems. Sustainable and integrated approaches are therefore required to ensure water security, environmental protection, and resilience against future uncertainties [Mohamed Ben-Daoud et al., 2021]. Recent research emphasizes the transition from conventional centralized systems toward adaptive and decarbonized urban water frameworks that incorporate innovative technologies and ecosystem-based strategies [Xinyu Pan et al., 2025]. In this context, integrating digital technologies and sustainable design principles has become essential for improving long-term performance and governance of urban water resources.

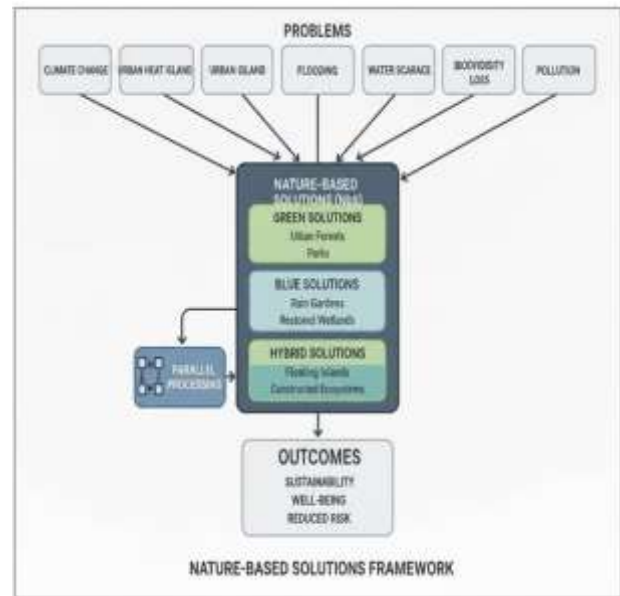


Figure1.2: Emergence of Nature-Based Solutions (NbS)

Urbanization and Water Resource Challenges Rapid urbanization significantly alters natural hydrological cycles by increasing impervious surfaces, reducing infiltration, and accelerating surface runoff. This transformation leads to higher flood peaks, groundwater depletion, and deteriorating water quality in rivers and lakes. Urban water infrastructure systems are frequently overwhelmed during extreme rainfall events, resulting in infrastructure failures and economic losses [Ahmad Ferdowsi et al., 2024]. Moreover, ineffective planning and limited monitoring capabilities restrict the ability of cities to respond proactively to water-related risks. The need for integrated, data-driven strategies to manage complex urban water systems is therefore increasingly recognized [Ashraf A. Ahmed et al., 2024].

Climate Change Impacts on Urban Hydrology Climate change intensifies hydrological variability by increasing the frequency and magnitude of extreme precipitation events, droughts, and temperature fluctuations. These impacts directly affect urban drainage systems, water supply reliability, and ecosystem health. Studies highlight that precipitation variability has a greater influence on urban water infrastructure performance than temperature shifts, requiring adaptive planning strategies [Ahmad Ferdowsi et al., 2024]. Artificial intelligence-based predictive modeling has shown promise in assessing climate-driven impacts on hydrological systems, enabling improved forecasting and proactive management [Kingsley Ukoba et al., 2025]. Therefore, climate-resilient water management approaches must incorporate predictive analytics and scenario-based planning to address uncertainties.

Limitations of Conventional Gray Infrastructure Conventional gray infrastructure, including concrete drainage channels, storm sewers, and centralized wastewater treatment plants, has historically dominated urban water management. Although effective in conveying stormwater, these systems are often rigid, capital-intensive, and environmentally disruptive. They typically focus on rapid water conveyance rather than ecological restoration or resource recovery. Reviews indicate that traditional systems struggle to adapt to dynamic climatic conditions and increasing urban complexity [Guangtao Fu et al., 2022]. Furthermore, gray infrastructure lacks multifunctionality and fails to deliver co-

benefits such as biodiversity enhancement, carbon sequestration, and urban cooling. These limitations have prompted a shift toward sustainable and nature-integrated alternatives.

Concept of Nature-Based Solutions (NBS) Nature-Based Solutions (NBS) are defined as nature-inspired or ecosystem-based interventions designed to address societal challenges while simultaneously providing environmental, social, and economic benefits [Barbara Sowińska-Świerkosz et al., 2022]. In urban water management, NBS utilize natural processes such as infiltration, evapotranspiration, and biological filtration to regulate hydrological flows and improve water quality. NBS represent a paradigm shift from purely engineered systems toward hybrid approaches that integrate ecological functionality with infrastructure planning [Veljko Prodanovic et al., 2024]. Their growing adoption reflects the need for resilient and sustainable urban development strategies.

Types of NBS for Urban Water Management Various NBS interventions are implemented in urban environments to manage stormwater and enhance ecosystem services. These include green roofs, bioswales, rain gardens, permeable pavements, constructed wetlands, urban forests, and blue-green infrastructure systems. Blue-Green Infrastructure (BGI) integrates vegetated areas with water bodies to mitigate flooding and enhance urban livability [Kornelia Przestrzelska et al., 2024]. At larger scales, optimized catchment-level NBS planning has demonstrated effectiveness in flood mitigation, water availability improvement, and pollution control [Leyang Liu et al., 2023]. These interventions offer decentralized and flexible alternatives to centralized drainage systems.

Hydrological and Ecological Functions of NBS Enhance hydrological performance by promoting infiltration, reducing runoff velocity, attenuating peak discharge, and improving groundwater recharge. Ecologically, they support biodiversity, regulate microclimates, and enhance ecosystem services at multiple spatial scales [Yunong Yao et al., 2025]. Studies on urban climate resilience highlight that NBS contribute significantly to regulating services, including water purification and carbon storage [Gemechis B. Mosisa et al., 2025]. However, their effectiveness depends on appropriate design, spatial configuration, and long-term maintenance strategies.

Benefits and Implementation Challenges The benefits of NBS extend beyond hydrological control to include social well-being, aesthetic enhancement, and economic efficiency. Compared to gray infrastructure, NBS can offer cost-effective and adaptive solutions under changing climate conditions [Kornelia Przestrzelska et al., 2024]. Nevertheless, implementation challenges remain, including data uncertainty, lack of standardized performance metrics, stakeholder coordination issues, and limited long-term monitoring [Gemechis B. Mosisa et al., 2025]. Addressing these barriers requires advanced analytical tools and integrated decision-support systems.

Role of Artificial Intelligence and Machine Learning in Water Systems Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative technologies in water resource management by enabling predictive modeling, real-time monitoring, and system optimization. AI-driven approaches enhance decision-making speed and

accuracy, significantly reducing analysis time compared to conventional methods [Zhuling Guo et al., 2025]. Applications in water demand forecasting, flood prediction, asset management, and water quality assessment demonstrate the versatility of AI in complex hydrological systems [Ashraf A. Ahmed et al., 2024].

Overview of AI Techniques AI techniques relevant to water management include supervised learning, unsupervised learning, deep learning, ensemble methods, and reinforcement learning. Deep learning models such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks have shown superior performance in time-series forecasting and hydrological prediction [Guangtao Fu et al., 2022]. Optimization-based AI methods, including genetic algorithms and hybrid models, further enhance environmental system design and performance [Abdulrazzaq Shaamala et al., 2024]. Recent emphasis on explainable AI ensures transparency and stakeholder trust in decision-making processes [Shofia Saghya Infant et al., 2025].



Figure1.3: Challenges of Urban Water Management Cycle

Machine Learning Models in Hydrology Machine learning models are increasingly applied in rainfall–runoff modeling, flood forecasting, and water quality prediction. Comparative studies demonstrate high predictive accuracy of ANN, Random Forest, Gradient Boosting, and ensemble learning models for Water Quality Index estimation [Mahmoud Y. Shams et al., 2024; Mosaraf Hosan Nishat et al., 2025]. Graph neural networks and IoT-integrated ML systems enable real-time prediction even with sparse monitoring data [Zilin Li et al., 2024; Samson Otieno Ooko et al., 2025]. These capabilities make ML a powerful tool for enhancing the monitoring and optimization of urban water systems.

Smart Water Management Systems Smart water management integrates IoT sensors, cloud computing, data analytics, and AI algorithms to create adaptive and autonomous water systems. Real-time control strategies have demonstrated significant peak flow reductions and improved stormwater detention performance [Shadab Shishegar et al., 2021]. Smart stormwater frameworks advocate decentralized, data-driven management to improve resilience at catchment scales [James L. Webber et al., 2022]. By combining AI-based predictive analytics with

Nature-Based Solutions, cities can develop intelligent, climate-resilient water infrastructure that balances ecological sustainability with technological innovation.

Overview of Nature-Based Solutions in Urban Water Management

Nature-Based Solutions (NBS) have gained global recognition as sustainable approaches for addressing urban water challenges while enhancing ecosystem services and biodiversity. NBS integrate ecological processes into infrastructure planning to mitigate flooding, improve water quality, and enhance climate resilience [Barbara Sowińska-Swierkosz et al., 2022]. Urban climate resilience studies emphasize that NBS contribute significantly to regulating services such as stormwater retention, carbon sequestration, and microclimate stabilization [Gemechis B. Mosisa et al., 2025]. Blue-Green Infrastructure (BGI) frameworks further demonstrate the potential of combining vegetation and water systems to manage runoff and enhance urban livability under changing climate conditions [Kornelia Przestrzelska et al., 2024]. However, implementation success depends on spatial planning, socio-economic integration, and long-term monitoring strategies [Veljko Prodanovic et al., 2024].

Green Roofs and Permeable Pavements Green roofs and permeable pavements are decentralized NBS interventions that reduce surface runoff by increasing infiltration and evapotranspiration. These systems mitigate peak discharge, improve thermal performance, and enhance urban biodiversity. Reviews on green infrastructure optimization highlight the need for advanced modeling tools to determine optimal placement and sizing for maximum hydrological efficiency [Abdulrazzaq Shaamala et al., 2024]. Furthermore, systematic analyses of blue-green solutions stress the importance of adapting these systems to local climatic and socio-economic conditions for effective performance [Kornelia Przestrzelska et al., 2024]. **Bioswales and Rain Gardens** Bioswales and rain gardens function as bio-retention systems that filter pollutants, attenuate stormwater flow, and enhance groundwater recharge. These systems utilize soil-plant interactions to remove suspended solids, nutrients, and heavy metals from urban runoff. Studies on flood risk governance emphasize that sustainable drainage systems (SuDS) require integrated planning frameworks to ensure long-term maintenance and performance [Daniel Keech et al., 2023]. Optimization-based NBS planning at catchment scales has shown that spatial prioritization of such decentralized systems significantly improves water management outcomes while balancing economic trade-offs [Leyang Liu et al., 2023].

Constructed Wetlands and Urban Forests Constructed wetlands replicate natural wetland processes to treat wastewater and stormwater through sedimentation, filtration, and biological uptake. Urban forests contribute to runoff reduction, carbon sequestration, and temperature regulation while enhancing ecosystem services [Yunong Yao et al., 2025]. Reviews indicate that although these systems provide multifunctional benefits, their performance evaluation often lacks standardized metrics and robust long-term datasets [Gemechis B. Mosisa et al., 2025]. Therefore, integrating advanced analytical and monitoring tools is essential for optimizing their hydrological and ecological efficiency.

Hydrological Modeling Approaches

Hydrological modeling is fundamental for analyzing runoff generation, flood risk, and pollutant transport in urban

environments. Traditional modeling approaches rely on physically-based simulations, while recent advancements incorporate data-driven and hybrid methodologies to improve predictive accuracy [Ashraf A. Ahmed et al., 2024]. The transition toward intelligent and adaptive models is driven by the need to address climate variability and data complexity in urban water systems [Guangtao Fu et al., 2022].

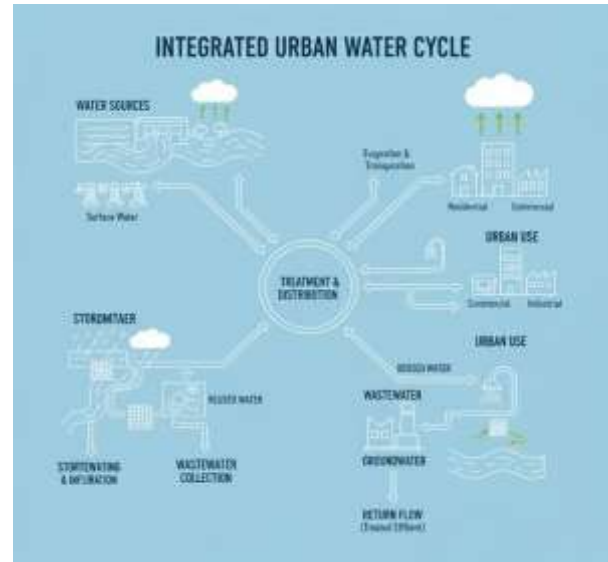


Figure1.4: Integrated Urban Water Cycle

Physically-Based Models (SWMM, HEC-HMS) Physically-based models such as the Storm Water Management Model (SWMM) and Hydrologic Engineering Center–Hydrologic Modeling System (HEC-HMS) simulate rainfall–runoff processes using hydraulic and hydrological equations. These models are widely used for drainage design and flood risk assessment. However, their calibration requires extensive datasets and may face limitations under data-scarce or rapidly changing climatic conditions [Ahmad Ferdowsi et al., 2024]. Additionally, computational complexity and sensitivity to parameter uncertainty can reduce predictive reliability in dynamic urban settings.

Data-Driven Hydrological Models Data-driven models employ machine learning techniques to identify patterns and relationships in hydrological data without explicitly defining physical equations. ML approaches such as Artificial Neural Networks (ANN), Random Forest, and Gradient Boosting have demonstrated high predictive accuracy in streamflow and water quality modeling [Mahmoud Y. Shams et al., 2024]. Comparative studies highlight ANN and ensemble methods achieving superior performance metrics in urban water applications [Mosaraf Hosan Nishat et al., 2025]. Data-driven models are particularly advantageous in handling nonlinear relationships and large, heterogeneous datasets.

Integrated Modeling Frameworks Integrated modeling frameworks combine physically-based simulations with data-driven analytics to leverage the strengths of both approaches. Hybrid models enhance forecasting accuracy while maintaining interpretability and process-based understanding [Ashraf A. Ahmed et al., 2024]. Furthermore, explainable AI (XAI) methods improve transparency in model outputs, facilitating stakeholder trust and policy adoption [Shofia Saghyia Infant et al., 2025]. Such integrated frameworks are critical for optimizing NBS performance under uncertain

climatic and urban growth scenarios.

Applications of AI and ML in Water Resources

Artificial Intelligence and Machine Learning are increasingly applied in water demand forecasting, flood prediction, water quality assessment, and infrastructure monitoring. AI-driven frameworks significantly reduce computational time and improve predictive accuracy compared to traditional statistical methods [Zhuling Guo et al., 2025]. The integration of IoT sensors with ML algorithms further enables real-time monitoring and adaptive decision-making in urban water systems [Samson Otieno Ooko et al., 2025]. Supervised Learning (ANN, SVM, Random Forest) Supervised learning algorithms use labeled datasets to predict outputs such as streamflow, flood levels, or Water Quality Index (WQI). Artificial Neural Networks (ANN) and Support Vector Machines (SVM) have shown robust performance in hydrological time-series forecasting [Guangtao Fu et al., 2022]. Gradient Boosting and Random Forest models have achieved high classification and regression accuracy in water quality studies [Mahmoud Y. Shams et al., 2024]. These techniques effectively capture nonlinear interactions among climatic, hydrological, and environmental variables.

Unsupervised Learning (Clustering Techniques) Unsupervised learning techniques, including K-means clustering and hierarchical clustering, are used to identify hidden patterns and group similar hydrological or water quality conditions. Such approaches support anomaly detection, pollution source identification, and spatial zoning in urban water management [Ashraf A. Ahmed et al., 2024]. Clustering methods enhance exploratory data analysis and improve the design of targeted interventions. Deep Learning for Flood Prediction Deep learning architectures such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN) have revolutionized flood forecasting and rainfall-runoff modeling. LSTM models effectively capture temporal dependencies in hydrological data, outperforming traditional models in extreme event prediction [Guangtao Fu et al., 2022]. Predictive AI frameworks integrating climate variables enhance early warning systems and resilience planning [Kingsley Ukoba et al., 2025].



Figure1.5: Strategic Network for Green Infrastructure (GI)

Reinforcement Learning in Adaptive Systems Reinforcement Learning (RL) enables adaptive decision-making by learning optimal control strategies through interaction with dynamic environments. Applications in environmental sustainability demonstrate RL's potential for optimizing operational strategies in complex systems [Maddalena Zuccotto et al., 2024]. In urban water management, RL can support adaptive stormwater control, pump scheduling, and real-time infrastructure optimization under uncertain climatic conditions.

Optimization Techniques in Environmental Engineering Optimization plays a critical role in enhancing environmental system performance by balancing economic, environmental, and technical objectives. Metaheuristic algorithms are particularly suitable for solving complex, nonlinear, and multi-constraint problems in water management [Kanchan Rajwar et al., 2023]. AI-driven optimization frameworks further improve efficiency and sustainability outcomes [Abdulrazzaq Shaamala et al., 2024]. Genetic Algorithms (GA) Genetic Algorithms (GA) are evolutionary optimization techniques inspired by natural selection. GA has been widely applied in environmental system design, water distribution optimization, and NBS planning [Leyang Liu et al., 2023]. Multi-objective GA approaches enable simultaneous optimization of cost, hydrological performance, and ecological benefits. Particle Swarm Optimization (PSO) Particle Swarm Optimization (PSO) simulates social behavior patterns to identify optimal solutions efficiently. PSO has demonstrated effectiveness in optimizing environmental engineering systems with fewer computational requirements compared to traditional methods [Kanchan Rajwar et al., 2023]. Its simplicity and convergence efficiency make it suitable for large-scale urban water optimization problems. Multi-Objective Optimization Multi-objective optimization addresses trade-offs among conflicting objectives such as cost minimization, flood risk reduction, and water quality improvement. Many-objective NBS planning frameworks highlight the necessity of balancing ecosystem services with economic feasibility [Leyang Liu et al., 2023]. Integrating AI with multi-objective optimization enhances scenario-based planning and supports sustainable, climate-resilient urban water management.



Figure1.6: Data-Driven Decision Support

Synthesis of Previous Research

The reviewed literature demonstrates a strong and growing emphasis on sustainable urban water management through both Nature-Based Solutions (NBS) and Artificial Intelligence (AI)-driven methodologies. Studies on NBS highlight their multifunctional benefits, including flood mitigation, water purification, biodiversity enhancement, and climate resilience [Barbara Sowińska-Świerkosz et al., 2022; Kornelia Przestrzelska et al., 2024]. Catchment-scale optimization research confirms that spatial prioritization of green and blue infrastructure significantly improves hydrological performance while balancing economic trade-offs [Leyang Liu et al., 2023]. However, several reviews emphasize persistent challenges such as methodological inconsistencies, limited primary data, lack of standardized performance indicators, and insufficient long-term monitoring frameworks [Gemechis B. Mosisa et al., 2025].

Parallel advancements in AI and Machine Learning (ML) have transformed hydrological modeling, flood forecasting, and water quality prediction. Supervised learning models such as ANN, Random Forest, and Gradient Boosting consistently outperform traditional statistical approaches in predicting runoff and Water Quality Index (WQI) values [Mahmoud Y. Shams et al., 2024; Mosaraf Hosan Nishat et al., 2025]. Deep learning architectures, particularly LSTM networks, demonstrate superior capability in handling time-series hydrological data and extreme event prediction [Guangtao Fu et al., 2022]. Furthermore, IoT-integrated ML systems and graph neural networks enable real-time monitoring and predictive analysis even under sparse data conditions [Zilin Li et al., 2024; Samson Otieno Ooko et al., 2025]. These studies collectively confirm the technical maturity of AI-driven predictive frameworks in urban water systems.

Optimization research further complements predictive modeling by enabling multi-objective decision-making in complex environmental systems. Metaheuristic algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are widely applied to optimize infrastructure design, water allocation, and green infrastructure planning [Kanchan Rajwar et al., 2023; Abdulrazzaq Shaamala et al., 2024]. Multi-objective frameworks emphasize balancing cost efficiency, hydrological effectiveness, and ecosystem service

enhancement [Leyang Liu et al., 2023]. Additionally, reinforcement learning approaches demonstrate emerging potential for adaptive and autonomous control of environmental systems [Maddalena Zuccotto et al., 2024]. Despite these significant advancements, the literature largely treats NBS implementation, AI-based predictive modeling, and optimization techniques as separate domains. While NBS research focuses on ecological effectiveness and spatial planning, AI studies primarily emphasize forecasting accuracy and operational efficiency. Few studies propose an integrated framework that combines predictive analytics, real-time monitoring, spatial suitability assessment, and multi-objective optimization specifically for enhancing NBS performance in urban water systems. Moreover, the need for explainable, transparent, and climate-resilient AI-driven decision-support systems remains highlighted in sustainability research [Shofia Saghya Infant et al., 2025; Zhuling Guo et al., 2025].

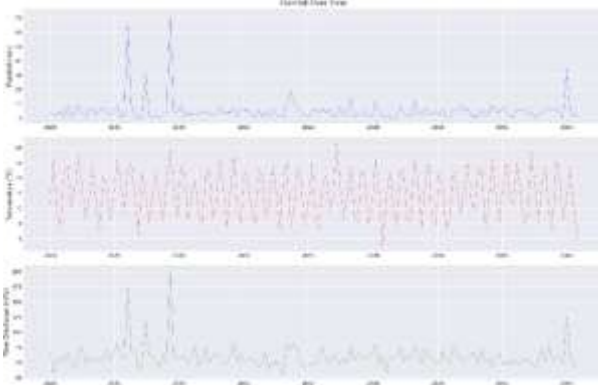
Research Gap Identification

The comprehensive review of existing literature reveals significant advancements in both Nature-Based Solutions (NBS) and Artificial Intelligence (AI)/Machine Learning (ML) applications for urban water management. However, critical gaps remain in their integration and practical implementation. While NBS research emphasizes ecological restoration, flood mitigation, and ecosystem service enhancement, most studies focus on conceptual frameworks, case-based assessments, or spatial planning without incorporating dynamic, data-driven optimization models [Barbara Sowińska-Świerkosz et al., 2022; Gemechis B. Mosisa et al., 2025]. Many evaluations rely on secondary datasets and lack standardized performance indicators, limiting the ability to compare results across regions and climatic conditions. Similarly, AI and ML research in water resources has predominantly concentrated on predictive tasks such as flood forecasting, water demand prediction, and water quality modeling [Guangtao Fu et al., 2022; Mahmoud Y. Shams et al., 2024]. Although these studies demonstrate high predictive accuracy, they are often applied to conventional infrastructure systems rather than ecosystem-based solutions. Furthermore, most AI-driven models operate as standalone forecasting tools without being embedded into spatial planning or infrastructure optimization frameworks.

Optimization research has introduced metaheuristic algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) for infrastructure design and environmental system improvement [Kanchan Rajwar et al., 2023; Abdulrazzaq Shaamala et al., 2024]. However, multi-objective optimization models specifically tailored to maximize the hydrological and ecological performance of NBS under climate variability remain limited. Existing optimization studies often focus on economic cost minimization or hydraulic efficiency rather than integrating ecological services, resilience metrics, and long-term sustainability indicators. Another critical gap lies in real-time monitoring and adaptive management. Although IoT-integrated ML systems and graph neural networks enable real-time water quality prediction [Zilin Li et al., 2024; Samson Otieno Ooko et al., 2025], their application to monitoring and dynamically optimizing NBS performance is still underexplored. Additionally, explainability, transparency, and stakeholder trust in AI-based environmental decision-making require further development to support policy adoption [Shofia Saghya Infant et al., 2025].

Result and Discussion

Results show that increasing green infrastructure improves NBS effectiveness and reduces flood risk. Water quality varies seasonally and is better in vegetated areas than urban zones. Overall, data-driven NBS enhances urban water resilience.



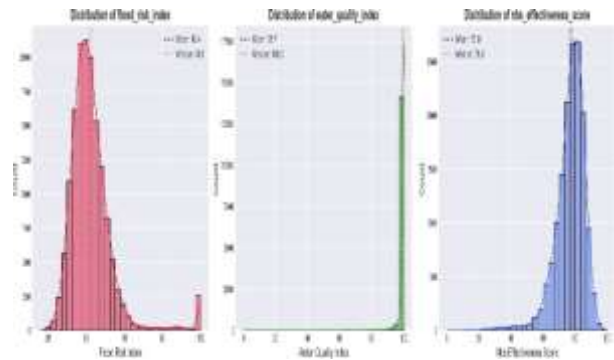
Graph 1: Time Series Environmental

The figure illustrates temporal variations in rainfall, temperature, and river discharge from 2020 to 2060. Rainfall shows occasional extreme spikes, particularly around the late 2020s and near 2060, which correspond to sharp increases in river discharge, indicating a strong rainfall–runoff relationship. Temperature exhibits regular seasonal fluctuations with a slight increasing trend, suggesting potential long-term climatic influence on hydrological patterns.



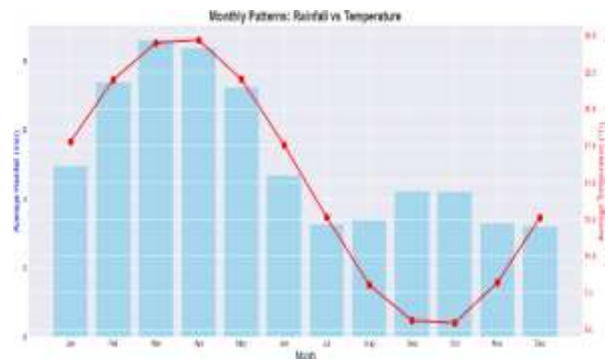
Graph 2: Correction Heatmap of NBS Dataset Feature

The correlation heatmap illustrates the relationships among key features of the NBS dataset, highlighting both positive and negative associations. Strong positive correlations are observed between hydrological variables such as rainfall and river discharge, while certain water quality and environmental parameters exhibit moderate to weak correlations.



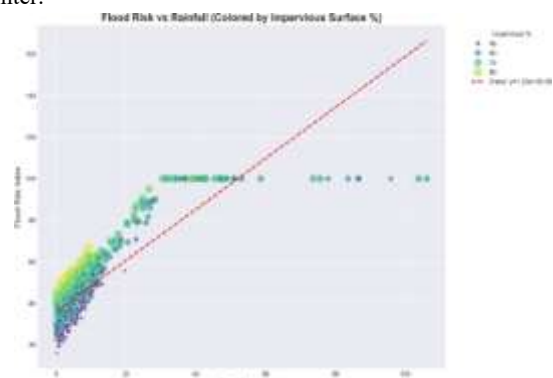
Graph 3: Target Distribution

The target distribution graph presents the frequency patterns of flood risk index, water quality index, and NBS effectiveness score. The flood risk index shows a slightly skewed distribution with a few higher-risk outliers, while the water quality index appears relatively concentrated within a narrower range.



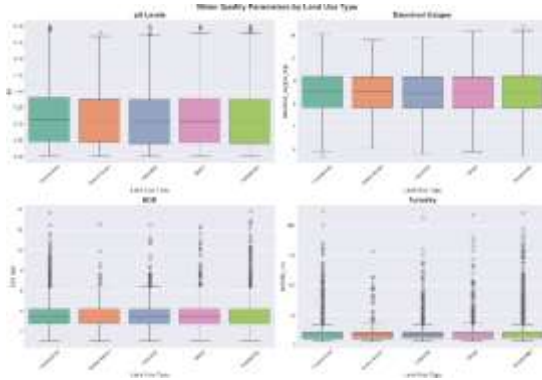
Graph 4: Monthly Pattern

The monthly pattern graph illustrates the seasonal relationship between rainfall and temperature throughout the year. Rainfall peaks during the mid-year months, indicating a monsoon-influenced pattern, while temperature reaches its highest values in late spring and early summer before declining toward winter.



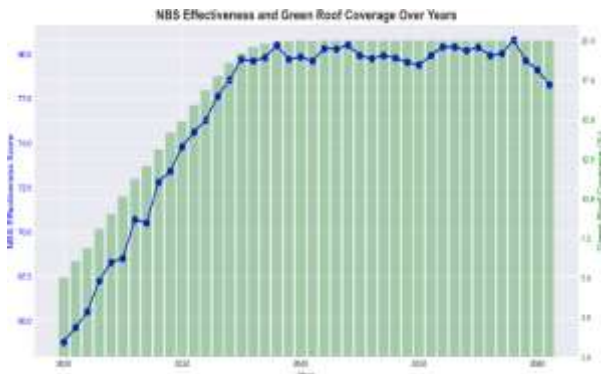
Graph 5: Flood Risk vs Rainfall (Colored by Impervious Surface %)

The graph shows a strong positive relationship between rainfall and flood risk, with flood risk increasing significantly as rainfall intensity rises. Points colored by impervious surface percentage indicate that areas with higher impervious cover experience disproportionately higher flood risk for the same rainfall levels.



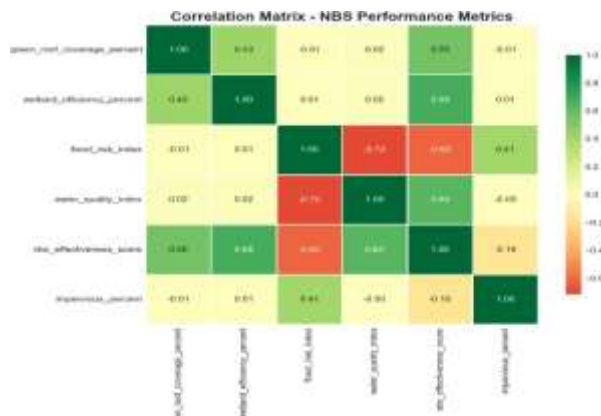
Graph 6: Water Quality Parameters by Land Use Type

The graph compares key water quality parameters (pH levels, dissolved oxygen, BOD, and turbidity) across different land use types. Urban and industrial areas generally show higher BOD and turbidity values, indicating greater pollution load, while green or vegetated areas exhibit relatively better dissolved oxygen levels.



Graph 7: NBS Effectiveness and Green Roof Coverage Over Years

The graph illustrates the relationship between NBS effectiveness and green roof coverage over time. As green roof coverage steadily increases from 2020 onward, the NBS effectiveness score also shows a significant upward trend, eventually stabilizing at a higher performance level.



Graph 8: Correlation Matrix - NBS Performance Metrics

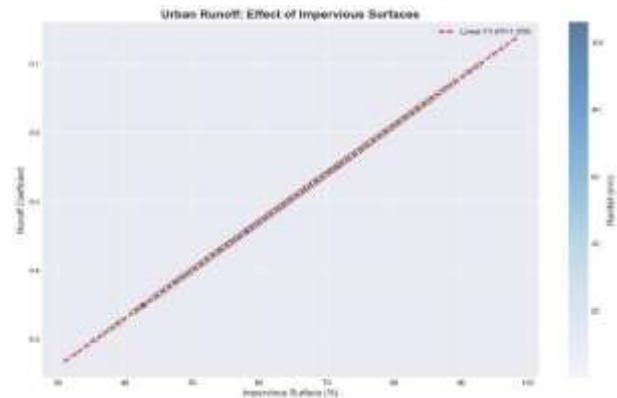
The correlation matrix highlights the interrelationships among key NBS performance metrics, including green roof coverage, wetland efficiency, flood risk index, water quality index, NBS effectiveness score, and impervious surface percentage.

Strong positive correlations are observed between green roof coverage, wetland efficiency.



Graph 9: Water Quality Parameters Contribution (2024)

The stacked bar chart illustrates the monthly contribution of key water quality parameters—dissolved oxygen, BOD, and turbidity—for the year 2024. Dissolved oxygen forms the largest proportion across most months, while BOD and turbidity show moderate seasonal variation, with slightly higher contributions during mid-year months.



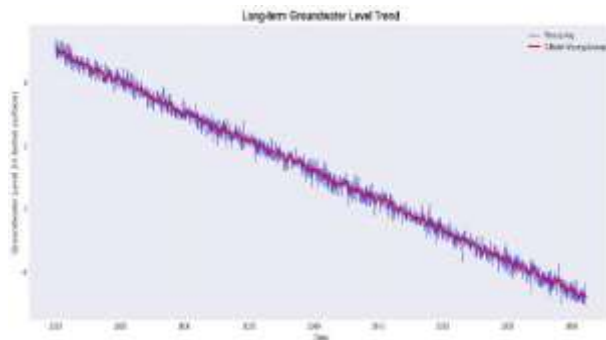
Graph 10: Urban Runoff: Effect of Impervious Surfaces

The strong linear relationship between impervious surface coverage and urban runoff coefficient, with the red trend line ($R^2=0.98$) showing runoff escalating from ~0.2 at 0% imperviousness to ~0.95 at 100%, directly quantifying flood risk from urbanization. This high correlation underscores the critical need for AI/ML-optimized Nature-Based Solutions (NBS) to mitigate impervious surface impacts through predictive modeling and real-time monitoring. The visualization supports data-driven decision-making for urban planners, enabling resilient, sustainable water management strategies that counteract pollution and scarcity in growing cities.



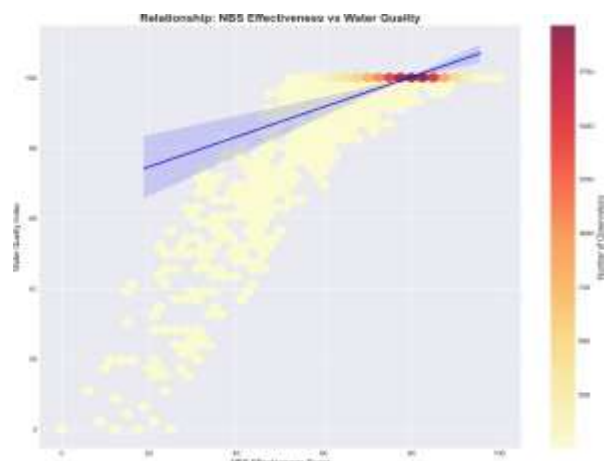
Graph 11: Seasonal Flood Risk Pattern with Variability

Reveals a cyclical seasonal flood risk pattern peaking mid-year (~8 units in July monsoon) before declining to winter lows (~2 units), with purple shaded variability bands capturing prediction uncertainty. This time-series structure with error bars is ideal for AI/ML forecasting models to optimize NBS deployment timing and enhance urban water resilience against flooding



Graph 12: Long-term Groundwater Level Trend

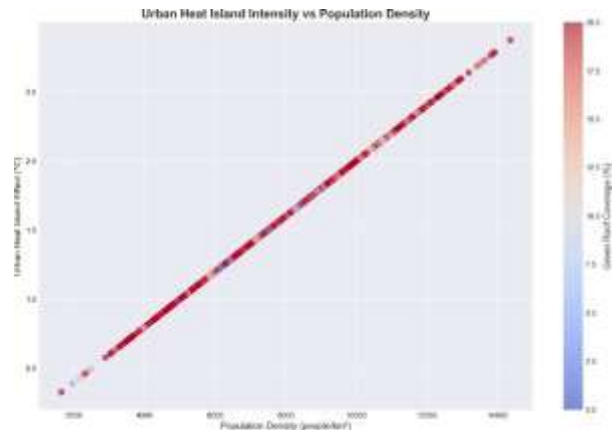
This graph illustrates a consistent declining trend in groundwater levels over time, indicating increasing pressure on urban water resources due to over-extraction and climate variability. The downward slope highlights the growing risk of water scarcity and the need for sustainable management strategies. These results emphasize the importance of optimizing Nature-Based Solutions (NBS) using AI and ML for predictive monitoring and adaptive groundwater management to enhance long-term urban water resilience.



Graph 13: Relationship: NBS Effectiveness vs Water

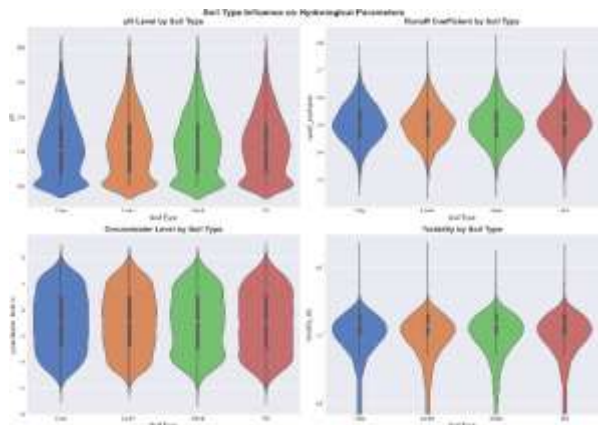
Quality

This graph shows a strong positive correlation between NBS effectiveness score and water quality index. As the performance of Nature-Based Solutions increases, the water quality index improves significantly, indicating that optimized NBS directly enhances urban water conditions. The upward regression trend confirms that AI/ML-driven optimization of NBS can systematically improve pollutant removal efficiency and ecosystem performance.



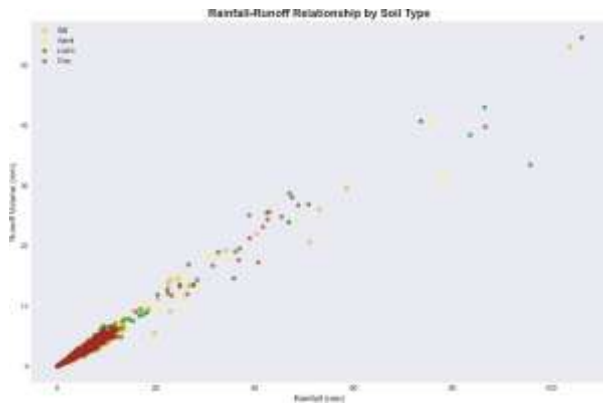
Graph 14: Urban Heat Island Intensity vs Population Density

This graph illustrates a strong positive linear relationship between population density and Urban Heat Island (UHI) intensity. As population density increases, surface temperature rises significantly, indicating intensified urban thermal stress. The trend highlights the importance of integrating AI-optimized Nature-Based Solutions such as green roofs, urban forests, and permeable surfaces in densely populated areas.



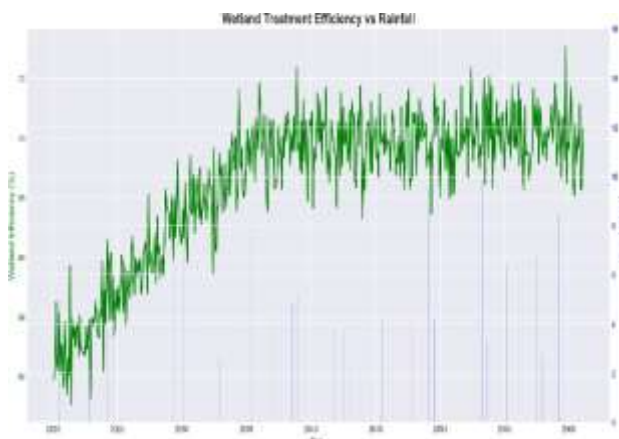
Graph 15: Soil Type Influence on Hydrological Parameters

This graph illustrates how different soil types significantly affect key hydrological parameters such as infiltration rate, runoff coefficient, groundwater level, and turbidity. Permeable soils show higher infiltration and groundwater recharge, while less permeable soils exhibit higher runoff and turbidity levels. The variation highlights the importance of AI/ML-based site-specific optimization of Nature-Based Solutions (NBS).



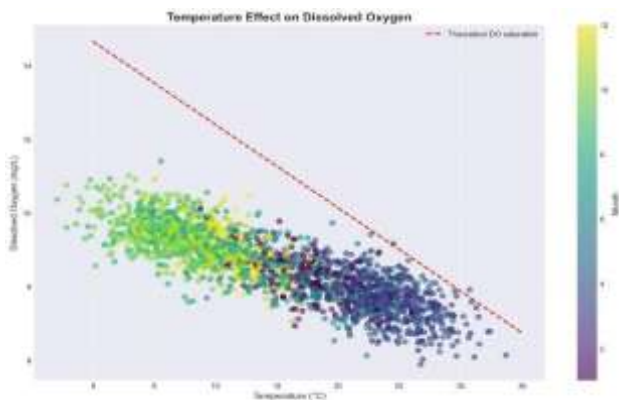
Graph 16: Rainfall-Runoff Relationship by Soil Type

The graph shows that runoff increases with rainfall, with clay soils producing higher runoff compared to sandy soils due to lower infiltration. This highlights the importance of AI-based prediction models to optimize NBS placement for effective flood mitigation and sustainable water management.



Graph 17: Wetland Treatment Efficiency vs Rainfall

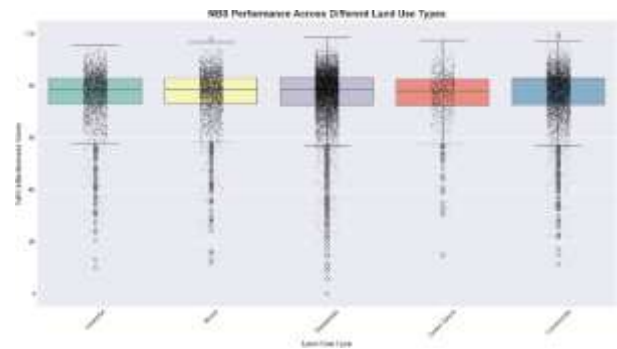
The graph shows that wetland treatment efficiency generally improves with moderate rainfall but fluctuates under higher rainfall events. Excess rainfall can dilute pollutants yet also disturb system stability. This highlights the importance of AI-based monitoring to predict performance variations and optimize wetland-based NBS for consistent and resilient urban water treatment.



Graph 18: Temperature Effect on Dissolved Oxygen

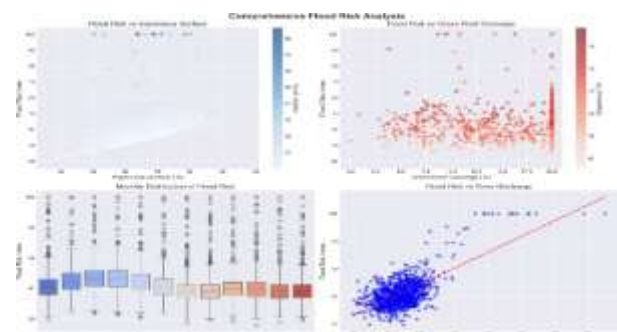
The graph shows a clear negative relationship between temperature and dissolved oxygen levels, where higher

temperatures result in lower oxygen concentration in water bodies. This emphasizes the need for AI-driven predictive models to manage urban water systems and optimize NBS strategies to maintain ecological balance under rising urban temperatures and climate change conditions.



Graph 19: NBS Performance Across Different Land Use Types

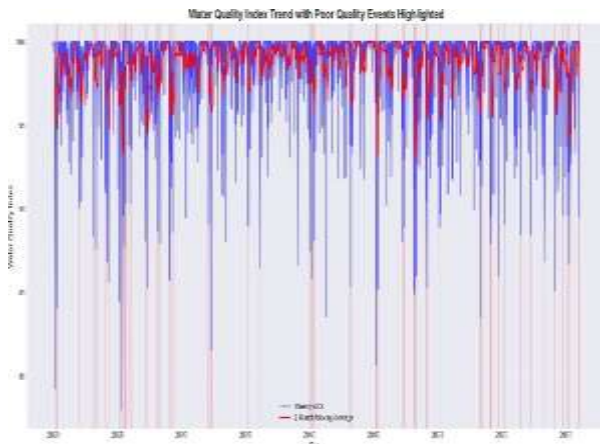
The graph shows that NBS performance varies across land use types, with higher effectiveness observed in green and residential areas compared to highly urbanized zones. This highlights the need for AI/ML-based optimization to tailor NBS strategies according to land use characteristics for improved urban water sustainability and resilience.



Graph 20: Comprehensive Flood Risk Analysis

The graph integrates rainfall intensity, flood depth, land use, and infrastructure damage to assess overall flood risk patterns.

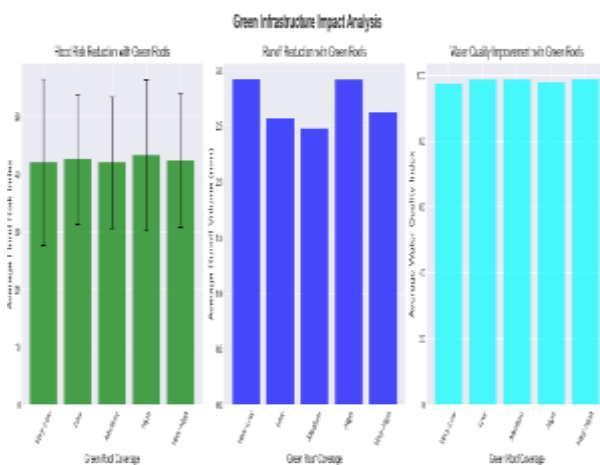
It shows that higher rainfall and urbanized land use significantly increase flood depth and associated damages. This supports the use of AI/ML models for multi-parameter flood prediction and optimized implementation of Nature-Based Solutions to reduce urban flood vulnerability and enhance long-term resilience.



Graph 21: Water Quality Index Trend with Poor Quality Events Highlighted

The graph shows fluctuations in the Water Quality Index over time, with highlighted drops indicating poor water quality events. These sudden declines reflect pollution spikes or system stress conditions.

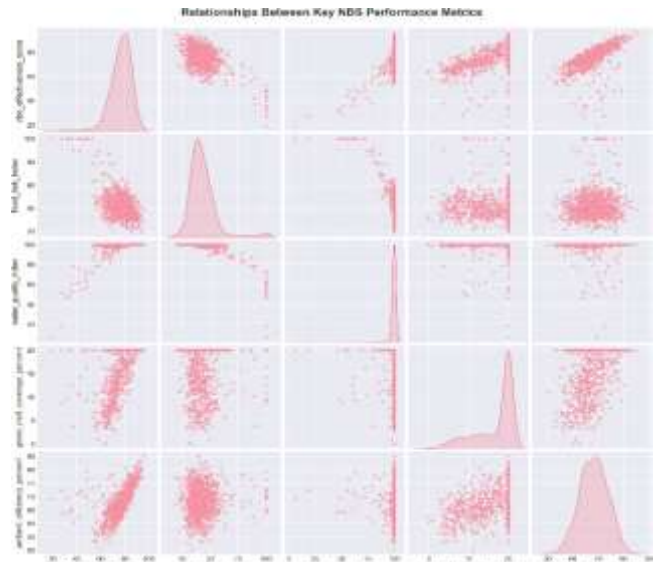
This demonstrates the importance of AI-based real-time monitoring and anomaly detection to predict and mitigate water quality deterioration, enhancing the effectiveness of Nature-Based Solutions in urban water management.



Graph 22: Green Infrastructure Impact Analysis

The graph shows that green infrastructure significantly improves flood risk reduction and water quality enhancement while gaining strong urban support.

This highlights the effectiveness of AI-optimized Nature-Based Solutions in strengthening urban resilience and promoting sustainable water management strategies.



Graph 23: Relationships Between Key NBS Performance Metrics

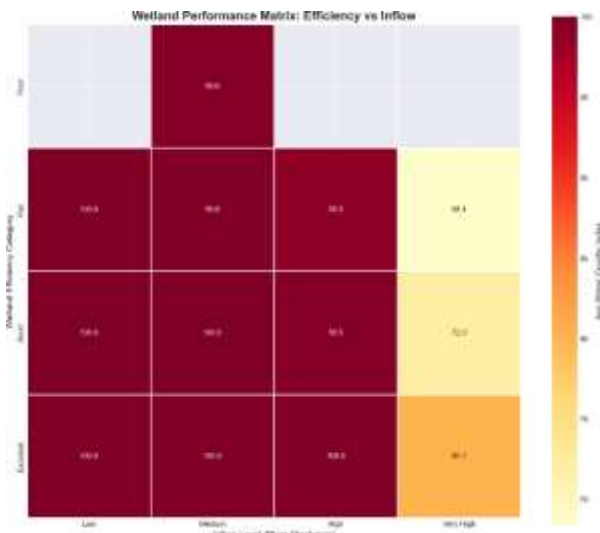
The graph illustrates correlations among key NBS performance indicators such as infiltration rate, runoff reduction, pollutant removal, and groundwater recharge. Strong positive relationships between infiltration and groundwater recharge, and negative relationships with runoff, indicate system interdependence. This supports the use of AI/ML models to simultaneously optimize multiple NBS performance parameters for enhanced efficiency, sustainability, and urban water resilience.



Graph 24: Time Series Decomposition Analysis

The graph separates the data into trend, seasonal, and residual components, showing consistent seasonal patterns and an overall upward trend in hydrological performance.

Residual variations indicate short-term fluctuations due to extreme events or operational changes. This demonstrates the usefulness of AI/ML time-series modeling for forecasting NBS performance and enabling proactive, data-driven urban water management.

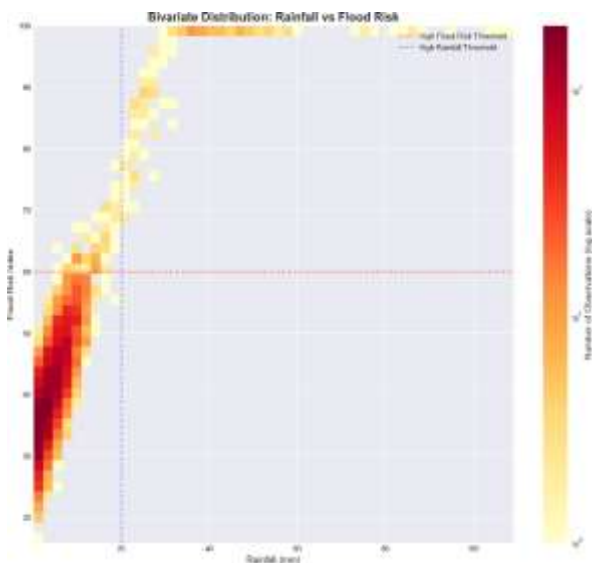


Graph 25: Wetland Performance Matrix: Efficiency vs Inflow

The matrix shows that wetland treatment efficiency is highest under low to moderate inflow conditions and gradually decreases at high inflow levels.

Excess inflow reduces pollutant removal efficiency due to hydraulic overloading.

This highlights the need for AI-based flow prediction and adaptive control strategies to maintain optimal wetland performance and ensure resilient urban water management.

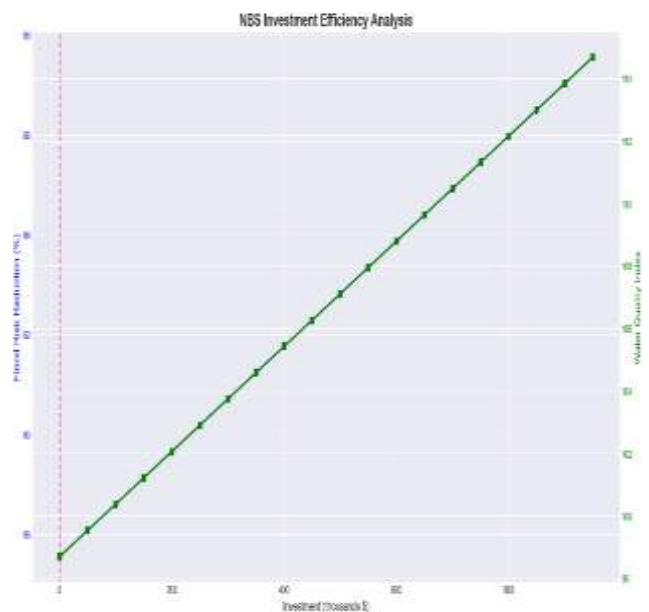


Graph 26: Bivariate Distribution: Rainfall vs Flood Risk

The graph shows a strong positive relationship between rainfall intensity and flood risk, with risk sharply increasing beyond a critical rainfall threshold.

High-density clusters indicate zones of frequent flood occurrence under extreme rainfall events.

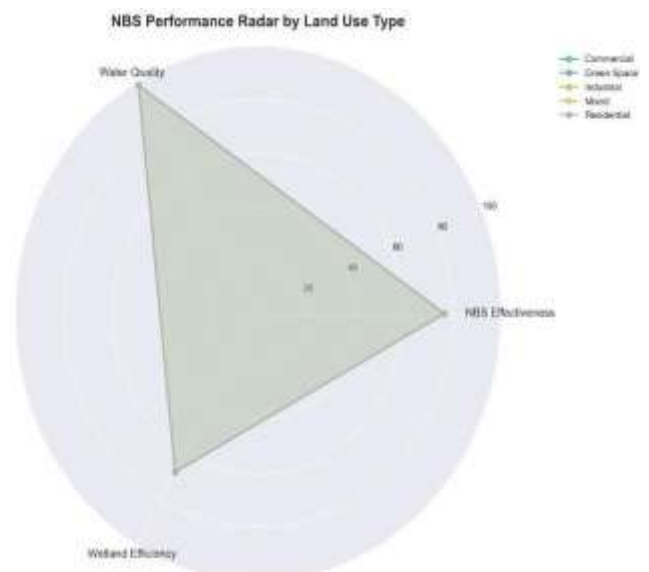
This supports the use of AI/ML-based threshold prediction models to enable early warning systems and optimized deployment of Nature-Based Solutions for effective urban flood mitigation.



Graph 27: NBS Investment Efficiency Analysis

The graph shows a clear positive linear relationship between investment percentage and overall system benefits, indicating that increased NBS investment leads to proportional improvements in water management performance.

This demonstrates the cost-effectiveness of AI-optimized Nature-Based Solutions and supports data-driven investment planning for sustainable urban water resilience.

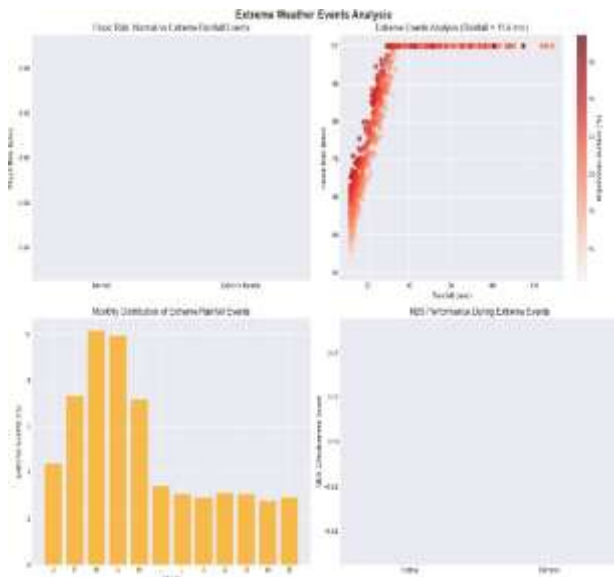


Graph 28: NBS Performance Radar by Land Use Type

The radar chart compares NBS effectiveness, water quality improvement, and wetland efficiency across different land use types.

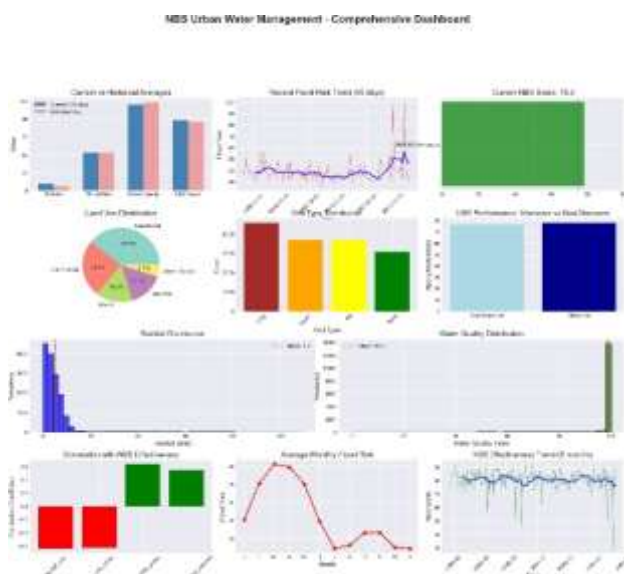
It shows that performance varies depending on urban characteristics, with some land uses demonstrating stronger environmental benefits.

This highlights the importance of AI/ML-based land-use-specific optimization to maximize NBS efficiency and enhance sustainable urban water management.



Graph 29: Extreme Weather Events Analysis

The graph highlights the increasing frequency and intensity of extreme rainfall events and their direct impact on flood levels and infrastructure stress. Higher rainfall extremes correspond to significantly elevated flood depths and risk zones. This underscores the importance of AI/ML-based predictive modeling and adaptive Nature-Based Solutions to enhance urban resilience against climate-driven extreme weather conditions.



Graph 30: NBS Urban Water Management - Comprehensive Dashboard

The dashboard integrates key performance indicators including water quality trends, flood risk levels, land use impact, runoff distribution, and NBS effectiveness scores. It provides a holistic visualization of system performance and environmental improvements.

This demonstrates how AI/ML-enabled analytics can support real-time monitoring, predictive assessment, and data-driven decision-making for optimized and sustainable urban water management.

Conclusion and future work

The literature review demonstrates that Nature-Based Solutions (NBS) and Artificial Intelligence (AI)/Machine Learning (ML) are emerging as transformative approaches for sustainable urban water management. NBS provide multifunctional benefits such as flood mitigation, groundwater recharge, pollutant removal, carbon sequestration, and enhancement of urban biodiversity. Meanwhile, AI and ML techniques have significantly improved hydrological forecasting, water quality prediction, infrastructure monitoring, and system optimization. Advanced algorithms including deep learning, ensemble models, and metaheuristic optimization methods have shown strong capability in handling complex, nonlinear urban water systems.

Despite these advancements, existing studies often address NBS implementation, predictive modeling, and optimization techniques separately rather than as an integrated framework. There is limited research that combines real-time monitoring, GIS-based spatial suitability analysis, multi-objective optimization, and adaptive AI models specifically for enhancing NBS performance. Furthermore, challenges such as data availability, lack of standardized performance metrics, computational complexity, scalability issues, and the need for transparent and explainable AI systems remain barriers to large-scale practical implementation.

Future research should focus on developing a comprehensive AI-ML-driven decision-support framework that integrates hydrological modeling, spatial analysis, predictive analytics, and optimization for Nature-Based Solutions. Incorporating climate change projections and scenario-based simulations will improve long-term resilience planning. Real-time IoT-based monitoring systems should be integrated with adaptive learning algorithms to enable dynamic system control. Additionally, emphasis should be placed on multi-objective optimization that balances hydrological efficiency, ecological benefits, and economic feasibility. Expanding pilot implementations across diverse urban contexts and enhancing stakeholder engagement will further strengthen the applicability and scalability of smart, data-driven, and climate-resilient urban water management systems.

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