

Artificial Intelligence and Machine Learning in Water Resources and Environmental Engineering: A Systematic Review and Future Research Agenda

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Abstract: Artificial Intelligence (AI) and Machine Learning (ML) are now leading-edge technologies being used to develop new ways to manage water resources and environmental engineering that outperform traditional statistical models by leveraging their capacity to manage nonlinear dynamics and large-scale multivariate datasets. The purpose of this systematic review is to determine the current status of AI/ML applications in the context of each method using a structured approach to synthesizing available evidence from primary databases such as Scopus and Web of Science. The methodologies used in this review are divided into a central taxonomy: predictive modeling using supervised learning; discovering patterns through unsupervised learning; making adaptive decisions using RL; and example hybrid models which use both analytical and data-driven algorithms.

There are many insights to be gained from this research study artificial intelligence(AI) has shown a high degree of accuracy in making flood predictions across various locations worldwide by means of Long Short-Term Memory neural networks (LSTM), with some reported values being nearly 99 % Nash-Sutcliffe Efficiency for specific locations in the tropics [1]; however, these findings must be interpreted carefully since they lacked adequate evaluation and were based only on one region where there was sufficient historical data, whereas this may not hold true in an area where little or no historical data exist and because these different types of locations of evaluating AI's use. Along with AI, Internet of Things (IoT) devices have enabled real-time monitoring of water quality with close to .99 precision. AI is being used in the field of environmental engineering for automation of sorting waste with accuracy's above 95% in the transition toward a circular economy. A significant hole remains in our knowledge regarding the advancement of AI/ML technology in water resources and environmental engineering. The vast majority of studies devoted to studying AI/ML in the water resources and environmental engineering industries utilize various AI/ML models to perform predictions of future conditions; however, few of these studies look at real-life applications for these AI/ML technologies or how they will be implemented at scale in countries that have limited access to quality data, such as Middle Eastern and dry developing countries. This gap was the motivation behind conducting this review; to consolidate evidence related to generalizability of model outputs, the need for open access data, and the movement from purely predictive models to decision-support systems. Nevertheless, critical challenges continue to exist such as reproducibility problems that arise from lack of freely available datasets/ code and lack of interpretability caused by complexity of deep neural net models. To resolve these drawbacks, the present review recommends: (i) To adopt PIML for improved accuracy through enforcing prior laws of physics within a ML model as well as increased clarity regarding the underlying mechanism of an ML prediction. (ii) Create a standardized data-sharing protocol to enable the use of benchmark datasets that are identified across the community. (iii) Use XAI techniques (SHAP and LIME) to better align an ML model's predictions with how



stakeholders are using those predictions for their decisions. (iv) Increase research on transfer learning strategies to improve the applicability of ML models in areas where there is limited data climate variation. All four of these approaches are the directions of future research proposed in this article.

Keywords: Artificial intelligence; machine learning; environmental engineering; water resources

1. Introduction

The water resource and environmental engineering sectors are under unprecedented stress due to the rapid urbanization, population growth and climate change that has caused hydrologic variability on a global scale. Classical hydrological models and traditional statistical procedures are the backbone of the hydrologic modeling community; however, their inability to produce reasonable representations of the modelling of modern complex environmental systems, due to the nonlinear nature of hydrologic processes, the spatial heterogeneity and temporal variability of hydrological events, has resulted in them becoming increasingly less useful when applied to contemporary hydrologic systems [2], [3].

Artificial intelligence (AI) and machine learning (ML) are being utilized as novel modelling methods that offer potential solutions to the limitations of traditional modelling methods due to their ability to learn from extensive multivariate datasets without requiring the explicit derivation of the coefficient equations used in developing traditional hydrologic models. Examples of successful ML modelling methods include deep learning methods such as the long short-term memory (LSTM) networks and convolutional neural networks (CNN) and transformer models [4], [5]. ML ensemble methods, such as random forests and XGBoost, have also provided superior predictive performance relative to traditional modelling methods for a variety of hydrologic and environmental modelling applications including flood forecasting, water quality assessment, groundwater elevation forecasting, irrigation maximization and ecological assessments.

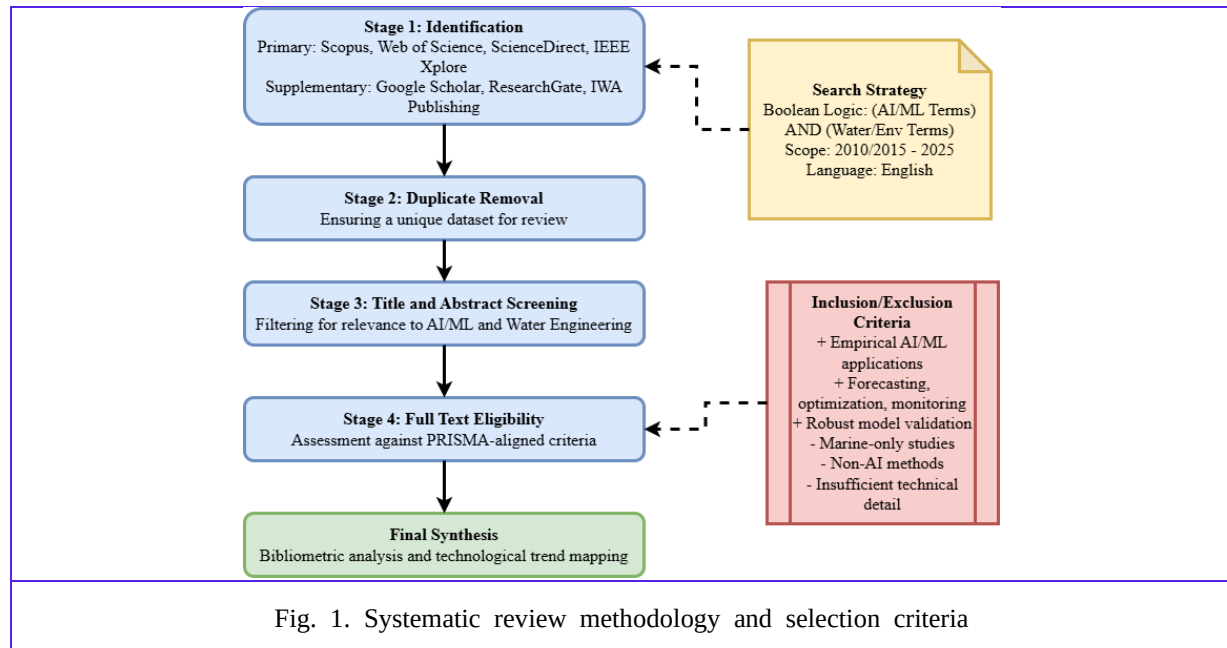
AI has been integrated into IoT and remote sensors which have made Environmental Monitoring much larger than ever before and it allows us to actually take data about the environment in real time and also across great distances to identify things that aren't right on scales and resolutions that would not have been possible without the use of AI technology [4], [5] [6]. Also, there has been an incredible increase in the number of publications related to applying AI techniques (Machine Learning, particularly) to water resources and environmental engineering in the past decade, creating a need to synthesize the research at the level of knowledge about how we use AI in these areas in order to identify common methods used in research studies, establish benchmarks for performance, highlight and summarize the most critical issues facing researchers today and provide guidance for future research directions [2], [3]. AI/ML techniques (like deep neural networks, convolutional neural networks, long short-term memory networks, random forests, support vector machines, adaptive neuro-fuzzy inference systems, ensemble/hybrid models) can outperform standard statistical or mechanical models for tasks that require non-linear dynamics or very large-scale multivariate data. Hybrid approaches integrate physical knowledge with machine learning algorithms, which provide for better bias correction of hydrologic projections and improved model robustness under conditions of data scarcity [7], [8]. AI-driven systems are changing the way that monitor water quality, using a combination of IoT sensor networks and satellite remote sensing for real-time detection of anomalies and predictive modeling [3], [5]. These systems achieve up to 94% accuracy in their predictions and can reduce the cost of field sampling by as much as 60% [3]. Applications include surface water quality assessments [9], groundwater level forecasting [10], [11], river/lake temperature forecasting [12], dam seepage analysis [13], optimizing wastewater treatment processes [14], managing aquaculture operations [15], scheduling irrigation [16], [17], forecasting for flooding and/or drought events [6], detecting macroplastic litter, etc. The integration of Artificial Intelligence (AI) and Internet of Things (IoT) allows for the ongoing surveillance of geographically dispersed environmental data, which provides improved data reliability when making well-informed decisions related to urban or rural settings. Additionally, the use of remote sensing will enhance the automated extraction of water body characteristics from multi-spectral images, leading to improved assessment of entire regions' ecosystems. Furthermore, transfer learning is being used more frequently to adapt models between different areas or disciplines where available training samples are scarce [5], [18], [19], [20]. Although AI has made enormous inroads as a

technology, there are still many significant barriers that have impeded the ability to implement and leverage AI as an integral tool within this domain. The most pressing issue currently is the reproducibility crisis, primarily due to the continued lack of open-source data sets and code sharing by researchers, which hinders any independent validation of the results obtained with research conducted using AI. Additionally, the complexity of many AI models means that they are often perceived as being "black box," and as such, there exists an interpretability gap between the model outputs and the ability of data users to trust or take action based on those results. The lack of transparency is further complicated by the fact that many researchers fail to consider the impact of human-induced factors (for example, urbanization, dam operations, etc.) when developing their models, and thus their models lack any credibility [2], [7], [8].

Researchers are also faced with the challenges posed by there being no standardisation on how to acquire and use data, resulting in very fragmented and inconsistent research across the domain. As a result, for the most part, there are results from many studies that have been successfully achieved in a controlled simulation or pilot study environment, but there are very few real-world applications of AI in any meaningful way. Researchers also need to face increasing ethical dilemmas related to the use of sensitive sensor data, as well as the many environmental impacts associated with AI, especially with regard to the carbon footprint of training and supporting very large AI models [3], [5]. While the research literature on AI/ML continues to grow exponentially, there are still many unresolved critical issues with the current state of knowledge. First is the widespread problem of reproducibility—much of the published literature does not include any sharing of datasets and/or source code, making independent verification incredibly difficult [2], [7]. Secondly, much of the research and application of AI/ML occurs at a very localized level and is often validated in a single geographic or climate area; this creates significant limitations on how applicable and generalizable these findings can be when used in areas subject to water stress like Iraq and the Middle East overall, where few locally-calibrated models exist [3], [21]. Thirdly, the "black box" phenomenon associated with many of the deep learning algorithms results in an interpretability concern that diminishes trust by stakeholders and inhibits integration of AI/ML into operational decision-making processes [22]. Fourth, there is little to no standardization in terms of data acquisition methodology, model evaluation metrics, or reporting protocol, leading to disparate, incomparable evidence published within the AI/ML literature [23]. To address these problems, this article aims to compile and share knowledge about all artificial intelligence and machine learning applications and associated technologies through a standardized databank using a structured taxonomy, to evaluate critically the quality of research evidence related to key performance indications, and develop a comprehensive research agenda aimed at addressing the identified limitations in the current scientific literature on these types of applications and associated technologies.

2. A structured, systematic review framework

This study processes the use of a structured systematic review framework to provide transparent, reproducible, and complete evidence for the application of Artificial Intelligence (AI) and Machine Learning (ML) in relation to Water and Environmental Engineering practices (see Fig.1).

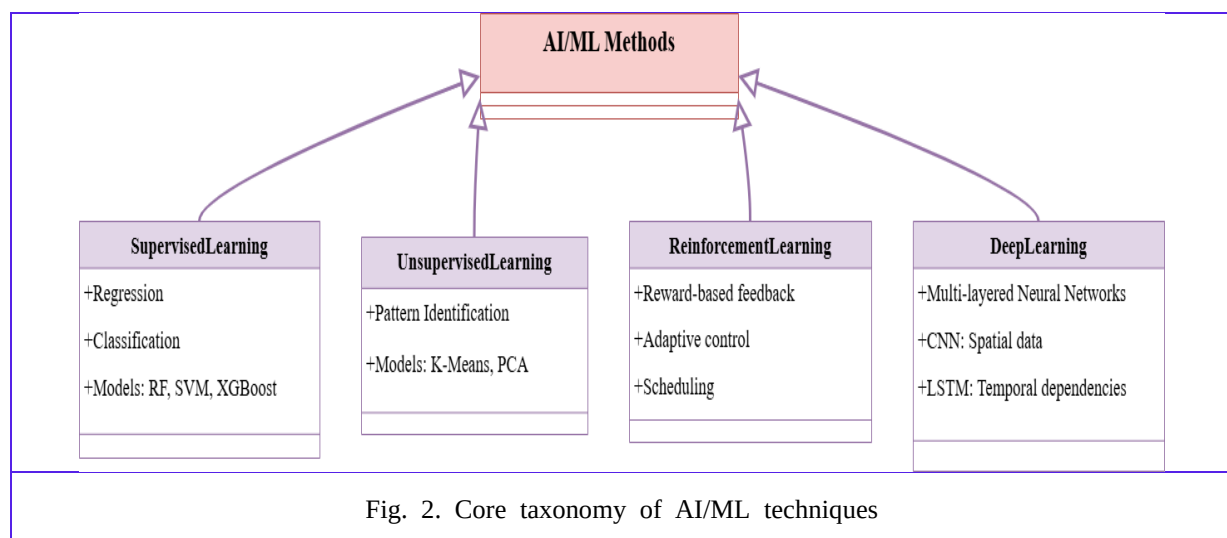


3. Taxonomy of AI/ML Techniques

Data analysis, prediction, and decisions are greatly enhanced and made more effective and efficient through Artificial Intelligence (AI) or machine learning (ML) technologies. The decision-making process uses improved data, and as such, has been greatly enhanced for scientific, engineering, and environmental applications in the past few years [14], [24].

The organization within the taxonomy of AI/ML techniques provides categories of AI/ML techniques, including: (a) supervised learning (e.g., regression, classification using Random Forests, Support Vector Machines and XGBoost), (b) deep learning (e.g., CNNs for depth and location or LSTMs for time and sequence), (c) unsupervised learning (e.g., clustering with k-means for location and detection of outliers), (d) reinforcement learning (for adaptive decision-making with water and resource operations), and (e) hybrid models that include AI and physics-based techniques (i.e., Physics-Informed Machine Learning) [25], [26], [27], [28], [29], [30]. The current landscape of AI and ML Taxonomies, including applications and strengths and weaknesses, and future directions, is summarized in this review.

The literature consistently categorizes AI/ML methods into four main groups, as shown in Fig.2.



3.1 Supervised Learning

Modern predictive modeling is based on supervised learning, and it works by predicting a response from an input. An algorithm receives training data that includes input-output pairs (where the input has a response given) that help the algorithm find patterns or relationships between the data elements and classify them into either discrete groups (classification) or continuous values (regression). The training data is used to compute a "ground truth" (examples with known responses), which allows the system to learn patterns in the example sets and develop a predictive model that is based on those patterns [31], [32].

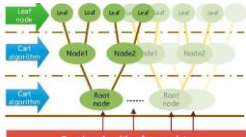
An example of a supervised learning algorithm is the Decision Tree (DT) and K-nearest neighbour (KNN). The Decision Tree is a systematic approach to gathering and analyzing data, where each node represents a feature in the dataset, and the branches represent the possible future values of the input feature. This allows humans to easily interpret the DT tree as they work through multiple decision points to determine their options.

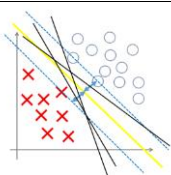
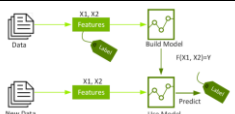
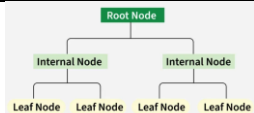
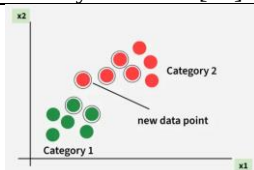
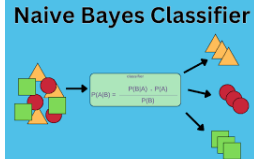
On the other hand, the K-nearest neighbour (KNN) algorithm is a "lazy learner" because it does not create a formal model until there is a prediction required; therefore, it relies on the relative proximity of the target input to determine how close it is to a training example with the same target feature value. For complex datasets, SVMs (Support Vector Machines) and Gaussian Naïve Bayes (GNB) are different mathematical ways to look at how to group things (i.e., classification). SVMs are very good at finding the best "boundaries (or hyperplanes)" between different classes so that they have as much space as possible between them, making them useful when working with data containing many dimensions. GNBs are based on the assumption that features will follow a normal distribution and will be mutually exclusive; therefore, they use probabilistic approaches to determine how to categorize objects. Even though this assumption generally does not hold true in practice, GNBs can still produce good results when finished with a project, such as classifying documents and analyzing sentiment within them[33], [34], [35].

Sometimes, ensemble methods can provide the best overall classification results. Random Forests (RF) and Extreme Gradient Boosting (XGBoost) are examples of ensemble methods; they utilize the "power of many" to achieve their classification tasks. An RF partitions the data into a multitude of independent decision trees that provide their respective classifications; thus, combining results will improve overall accuracy and reduce the chance of overfitting independent variables. On the other hand, an XGBoost algorithm builds trees in sequence, with each tree designed to make up for the deficiencies in the previous tree(s); therefore, after the sequential development of all trees, the combined results yield a very accurate classification model (XGBoost is considered one of the preeminent tools used in data science today)[36], [37], [38].

Supervised learning techniques have consistently shown excellent accuracy across water-resource and environmental disciplines. For example, Random Forest classifiers have attained an estimated 0.89 accuracy for air quality index classification [39]; Support Vector Machines have been used to predict water quality from ungauged river catchments with comparable results [34]. Similarly, XGBoost has been thoroughly evaluated for hydrological streamflow forecasts, outperforming single decision tree methods regarding generalizability in situations where there is limited data [8]. LSTM-based supervised deep learning applied to flood predictions at multi-day intervals throughout tropical basins has achieved Nash–Sutcliffe efficiency (NSE) values over 99% [1]; however, the evaluation of such results should also consider the calibration dataset as well as the characteristics of the basin itself.

Table 1. Supervised learning algorithms

Algorithm	Task Type	Core Logic	Main Advantage	Main Drawback	Algorithm Diagram
RF	Class. & Reg.	Collection of various independent decision trees.	Extremely precise; does not allow for outlier data.	High processing requirements; opaque decision-making.	

					Architecture of the Random Forest ensemble model [36]
SVM	Class. (mostly)	To establish the most effective dividing line (or hyperplane).	Excellent for a massive amount of pure data.	Most ineffective on data that contain many conflicting features or noise.	 Optimization of the decision boundary in a Support Vector Machine (SVM) [35]
XGBoost	Class. & Reg.	Every tree helps to correct errors made by previous trees through its addition to the ensemble.	The fastest speed and greatest accuracy.	Difficult to adjust; often fit the data too closely.	 Workflow of a supervised machine learning pipeline [40]
Decision Trees	Class. & Reg.	Sometimes called flowchart style or logic-based splits.	Very simple to understand and illustrate.	Large potential for fitting to training data.	 Structural hierarchy of a standard decision tree binary classifier [41]
KNN	Class. & Reg.	K closest points vote or average the resulting value.	Do not require time to train; simple to implement.	Make predictions very slowly; use lots of memory.	 Classification of an ambiguous query point using the k-Nearest Neighbors (k-NN) [42]
Naive Bayes	Classification	Probability-based rules (Bayes theorem).	Quick and easy for data of many sizes such as small amount of text.	Assumes all features are perfectly independent.	Naive Bayes Classifier  Naive Bayes model [43]

3.2 Unsupervised Learning

Unsupervised learning can be thought of as a method of discovering new data points from data. This means that the algorithm creates ways to find hidden structures in a dataset that has no pre-existing labels or "correct" answers. Unlike supervised learning, where there is a path that leads to a specific target, unsupervised methods will provide the user with patterns so that natural content groupings will occur, or will simplify the information in the dataset. The most recognized two categories of this type of approach are Clustering and Dimensionality Reduction, both of which will allow for the interpretation of high-

dimensional, non-structured/raw data [36], [37].

Clustering (K-Means being the most common example) takes a set of data points and divides them into distinct groups based upon commonality (similarity). In K-Means, an algorithm will iteratively determine a set of central points (centroids) that represent the center of each group of data points, and assign every data point to the center closest to it (nearest centroid). This has already been applied to a number of environmental and industrial applications, such as the zoning of water for quality purposes. By analyzing elements of data for variables, such as pH, turbidity, and chemical concentrations, K-Means can automatically categorize the various constructs in terms of water quality or identify extreme, unusual events in datasets by indicating that a data point is significantly farther from any centroid than a pre-determined threshold (an indication of possible contamination of the water source or sensor malfunction) [44].

Techniques such as Principal Component Analysis (PCA) are key to performing dimensionality reduction, which is the process of simplifying the data with little or no loss of meaning. Many datasets found in the real world will frequently have many dozens of variables, many of which are actually redundant or represent "noise." PCA mathematically transforms these numerous variables into a much smaller set of "Principal Components." In so doing, it allows researchers to visually represent vast quantities of complex, multidimensional data on a simple 2-dimensional or 3-dimensional plot. This visualization is particularly useful for identifying trends that may otherwise be buried among the multitude of data points in a typical large spreadsheet [45].

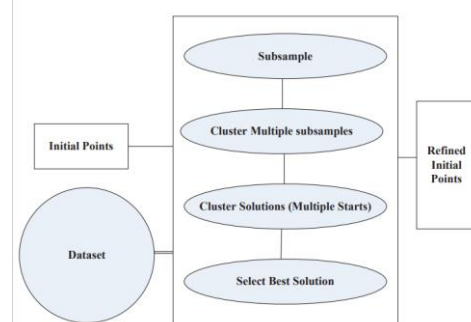
By combining these two sets of techniques, unsupervised learning provides an effective "lens" to give a clear view of raw data. In many cases, PCA will also be the first step in a sequence of analyses done prior to applying a clustering algorithm such as K-Means, where it is used to remove noise (i.e., the redundant and non-useful data items) and reduce complexity before the next step in the analysis is conducted. By utilizing these two complementary techniques together, the resulting clustering will be based on the most relevant patterns extracted from the data, resulting in improved classification, increased efficiency with respect to the storage of that data, and greater insight into the physical properties that govern the data being studied [20].

K-Means classification is one of the ways that have been used in environmental applications to do spatial zoning on water quality parameters, which allows automatic detection of contamination hotspots without needing labeled training data [44]. Additionally, PCA has served as preprocessing prior to reducing the high dimensionality of water quality datasets that involve multiple parameters which improved how quickly and easily downstream classification models can be developed from the multivariate datasets [45]. These methods are especially useful in areas where there is limited data available, such as dry or semi-dry areas that also lack reliable sensor infrastructure.

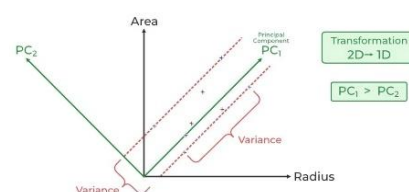
Table 2. Unsupervised learning algorithms

Algorithm	K-Means	PCA (Principal Component Analysis)
Core Logic	Splits data into K different groups while minimizing the distance between each point and the respective group (centroid) to discover membership patterns.	Rotates data into new axes (components). A new axis representing more variance versus other new axes represents less variance, representing less informational value.
Main Advantage	It is quick, easy, and can be used for large data sets.	It reduces noise so you are able to view very large amounts of high-dimensional data in 2D or 3D.
Use Case	Identifying zones of water quality, segmenting customers based on purchasing patterns, and detecting anomalies.	Prepping data for other models, compressing images, and visualizing the data.

Algorithm Diagram



Architectural workflow of the Bradley-Fayyad-Reina (BFR) K-means initialization method [45]



Dimensionality reduction from 2D to 1D via Principal Component Analysis (PCA) [44]

3.3 Reinforcement Learning

RL is a new approach to managing your water resources, particularly when it comes to making decisions and controlling systems that are complex and cannot be solved by traditional optimization techniques. Reinforcement Learning differs from traditional supervised learning because it enables the agent to learn from experience by interacting with either an artificial or a real-world environment, and receiving rewards and/or penalties based on actions taken for all of the tasks that are processed [46], [47]. Reinforcement Learning (RL) has an inherent benefit over traditional Stochastic Dynamic Programming methods, namely it helps address the "curse of dimensionality", a major limitation of these methods in hydrological engineering. RL can reduce user adjustments to input values in hydrological modeling (thus providing a more scalable and flexible model to work with), by using a search-based method and developing knowledge of the inherent stochastic nature of hydrological fluxes without requiring prior probabilities of transitioning between states, to develop out-of-model transition probabilities for RL agents in water management[46], [48].

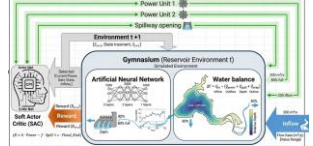
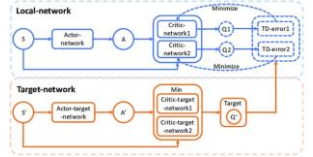
Reservoirs are heavily relied on for managing the supply of water, controlling floods, and generating energy. These three areas of water use all go through a balancing act with each other as the reservoir is managed over its entire service life with various mechanical and digital controls. In doing so, there must be clear guidelines and organizational procedures put into place for how these tasks are completed and the effects that occur as a result of these decisions, this is where RL comes into play. Multiple reservoirs have been studied and have utilized contemporary algorithms such as DDPG, DQN, SAC and multiple batch of RLs. The use of DDPG-based algorithms have been researched and applied to develop flexible operational plans, when taking into account all relevant variables when assessing operational plans, for the Chao Phraya River Basin. Some examples of variables include but are not limited to the current flow conditions downstream and projected inflows. Integrating batch-mode RL algorithms with hydrodynamic-ecological models have created opportunities to produce operational policies that achieve not only quantity objectives but also quality-related objectives. Examples of achieving quality-related objectives include, but are not limited to, managing dissolved oxygen concentrations and/or temperature in multi-outlet reservoirs [49], [50].

RL can optimize irrigation schedules while providing up-to-the-moment soil and climate data to implement water management strategies for precision ag. New frameworks of semi-centralized multi-agent reinforcement learning have been developed for providing distributed decision-making across large agriculture zones. The new performance metrics associated with these models have produced significant efficiency gains in agricultural water management, including a 4.0% decrease in water consumption without sacrificing crop yield, thus increasing the overall efficiency of irrigation water use [51]. Increasingly researchers are exploring sociohydrological modelling with reinforcement learning (RL) approaches that can account for complex, time-varying patterns of human-water interactions. The RL approach to water management uses retrospective evaluation to inform the future adaptation of water

management interventions. This is an exciting area of research that is providing increasing recognition of the generalisability, transferability and efficient data use in a variety of scales used for water management[46].

Quantified results from RL-assisted water management investigations confirm substantial benefits to performance: SAC aided hydropower optimization yielded a 9.43%-increase in economic production [52]; semi-centralized multi-agent RL-based irrigation scheduling produced a 4.0% reduction in water volume used while maintaining crop yield [51]. However, these studies were only done in simulated conditions, and therefore further research is required to validate through real-world operational application results previously achieved through simulation.

Table 3. Specific Reinforcement Learning Algorithms in Water Resources

Algorithm	Strength	Application	Performance Metric	Diagram
DDPG	Handles continuous actions	Multi-reservoir planning	High flexibility in release plans	 Architectural framework of a centralized multi-agent DDPG (MADDPG) variant [49]
SAC	Entropy-based exploration	Hydropower optimization	+9.43% economic gain	 Schematic layout of a reservoir management framework using the Soft Actor-Critic (SAC) [52]
TD3	Reduces overestimation	Single-reservoir control	Solves dimensionality issues	 Internal architecture of the Twin Delayed Deep Deterministic Policy Gradient (TD3) [53]
SCMARL	Distributed coordination	Irrigation scheduling	4.0% water savings	 Hierarchical multi-agent reinforcement learning (MARL) framework for distributed irrigation scheduling [51]

3.4 Hybrid Models

A hybrid model is actually a dramatic change for those of us that do research and work with water resources engineering, as they provide a middle ground between traditional and solely data-driven theories/models of water resources. Hybrid models are used to take advantage of both machine learning, which has the ability to predict and recognize patterns, as well as process based hydrologic models, which allow for a theoretical basis and a physical reason for the predictions and patterns identified through machine learning[39], [54].

The major reason for creating hybrid models is to overcome significant drawbacks associated with stand-alone modeling techniques. Models based solely on data are generally accurate in their training ranges but often contradict the laws of nature and do not properly extrapolate to new situations. On the other hand, physics-based models are physically consistent, but they have difficulties related to their computational efficiency (speed, memory usage, etc.) as well as difficulties capturing nonlinear and complex relationships in heterogeneous systems[55].

By embedding features related to practical experience, such as governing equations (laws), boundaries and conserved quantities, etc., Physics-Informed Machine Learning directly integrates physical knowledge into the machine learning framework. This provides the machine learners with sufficient information to constrain the machine learning outcome(s) so that the results are consistent with the physical model and enable the machine to utilize observational data for furthering its development.

Types of Hybrid Approaches: Firstly, Physics-Informed Neural Networks the PINN method incorporates physical restrictions into the loss function of deep learning models by including additional terms to penalize when an underlying governing physical rule (such as mass balance or energy conservation) is violated. As a result, these systems create solutions that are both consistent with observation-based data, and also agree with governing principles of theory on how a physical system should function. Secondly, Knowledge-Guided Deep Learning, this method utilizes one's understanding of the physical science to inform a number of elements within the modeling framework including model architecture, selection of feature variables, and training procedures. An example of a successful application of Knowledge-Guided deep learning is in the development of hydrologic model calibration. In this regard, knowledge of the physical science is utilized to inform the determination of parameters for conceptual hydrologic models (for instance, the Sacramento Soil Moisture Accounting Model) [56].

While Sequential and Parallel Hybridization, The Hybrid models may be composed of sequential (one model's output serves as input to another model) or parallel architectures (both models run at the same time and have their outputs merged together). One Table example would be the combination of a deep learning technique and a physics-based method for global hydrology modelling and showing how both improved the accuracy of simulating terrestrial water fluxes [57].

3.4.1 Application and performance

- Forecasting Streamflow:

Streamflow forecasting models designed on physical principles use physics to help produce accurate predictions and perform better than either data-driven or conceptual modelling. By limiting the degree of freedom available to the models with respect to the forces of nature, these models provide better generalization of streamflow across different climatic conditions and are able to retain a consistent hydrological relationship between rainfall and streamflow during droughts and hydrologic extremes[54].

- Evapotranspiration Estimation (Et)

Hybrid methodologies have proven effective for estimating actual evapotranspiration (Et) in complex processes such as those related to both energy balance and water supply. Models using hybrid approaches are able to account for the non-linear interaction of different meteorological parameters and vegetation characteristics better than traditional machine learning approaches do [55], [57].

- Groundwater Modelling

Data-driven deep learning approaches based on knowledge have been successfully applied to the calibration of groundwater models and have reduced the run-time of traditional techniques by up

to 99%, while producing results of comparable accuracy. These approaches make use of the physicochemical processes associated with groundwater to limit the amount of uncertainty in the parameters being used to create the model, thus making the optimization of the model a more efficient and effective process [39], [56].

Table 4, shows advantages over standalone approaches.

Table 4. Advantages over standalone approaches of hybrid models			
Aspect	Data-Driven Models	Physics-Based Models	Hybrid Models
Physical Consistency [39], [54]	Limited	High	High
Exploration Capability [55], [56]	Poor	Moderate	Improved
Computational Efficiency [56], [57]	High	Low	Moderate
Inheritability [54], [56]	Low	High	Moderate
Data requirements [55], [57]	High	Moderate	Moderate

3.5 Claims and Evidence for AI/ML Taxonomy

Table 5 summarizes how different human activities and processes have used AI and machine learning (ML) to manage freshwater resources and sustain water supply.

Table 5. The claims and evidence for AI/ML taxonomy			
Taxonomy Category	The Claim	Supporting Evidence	Strength of Evidence
Deep Learning	LSTMs, a type of recurrent architecture, are used for the majority of water related future forecasts that require strong dependence on past data over long periods of time.	Multiday flood predictions in tropical areas with LSTMs have achieved Nash-Sutcliffe efficiency of up to 99%. [1] LSTMs tend to outperform traditional ANNs for sequence-based tasks [58]	 Very high
Attention-Based Models	Transformers provide a better way to model long-term dependence in streamflow while circumventing problems due to vanishing gradients that exist when using RNNs.	Transformer models have demonstrated successful prediction performance over multiple datasets for both 24 and 120-hour streams, across a number of different hydrological datasets [59], [60]	 High
Ensemble and Classical ML	Both Random Forest and Support Vector Machines are very successful when it comes to classifying data into classes and/or predicting continuous values in situations where there is limited data available or limited resources to work with.	A classification accuracy of 0.89 was recorded with Random Forest models for air quality indices [61] and multi-parameter water quality assessments obtained 0.99 precision [62]	 High
Computer Vision	CNN architectures utilize two common types of CNN-based detection algorithms: YOLO (You Only Look Once) and Mask R	In addition to automatic detection of marine litter and oil spills with significant rates of detection [63], these methods	 Very high

4. Core Applications in Water Resources

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graph TD; A[Core Applications in Water Resources] --> B[Hydrology and Surface Water]; A --> C[Water Quality Monitoring]; A --> D[Smart Water Infrastructure]; B --> B1[LSTM Networks<br/>(99% NSE Flow Prediction)]; B --> B2[Transformer Architectures<br/>(Attention & Flood Events)]; C --> C1[ML + IoT Integration<br/>(RF/NN: 0.99 Precision)]; C --> C2[In Situ Optical Sensors<br/>(Pharmaceuticals & Pesticides)]; D --> D1[HydroSense Framework<br/>(Dual Microcontroller IoT)]; D --> D2[Urban Management<br/>(pH, DO, Nitrogen Levels)];
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Fig. 3. Core applications in water resources

Fig. 3. Core applications in water resources

Deep learning techniques are at the forefront of hydrology prediction. One example of a popular deep learning method has been Long Short-Term Memory (LSTM) networks see Fig.4, which excel at analysing time series data without losing vital past information. One of the characteristics that make LSTM networks so useful for hydrology forecasting is that their flow rate estimate accuracy has achieved Nash-Sutcliffe

efficiency scores of up to 99%. Although LSTMs have become a staple for how to implement LSTM networks, Transformer architectures as shown in Fig.5, are also emerging as alternatives for capturing long term dependent events through an “attention” mechanism. In fact, recent studies have successfully used Transformer architectures to leverage the historical data from upstream branches to accurately predict river water levels during periods of extreme flooding [1], [59].

Water shortages and changing hydrological patterns in dry and semi-dry areas like Iraq , Iran and the Middle East are huge obstacles for water management using AI (Artificial Intelligence) and ML (Machine Learning). Iraq's main rivers are the Tigris and Euphrates. There are many dams on these rivers, which means that the rivers are affected by the decreasing amount of water flow that was caused by climate change and the increase of saltwater, which creates very complex hydrology that has changed many times over and cannot be managed with old-fashioned models [3]. Iraqi scientists have been doing research on using Machine Learning to monitor the quality of water by creating IoT sensor networks to collect data paired with AI algorithms for the Shatt al-Arab Waterway and other Iraqi bodies of water [3]. One of the biggest hurdles to creating an accurate, locally calibrated AI model is the lack of a publicly accessible, long-term hydrology data set for all of the Iraqi watersheds. Transfer learning and physics-informed techniques provide viable ways to address this data shortfall in this region [20], [39].

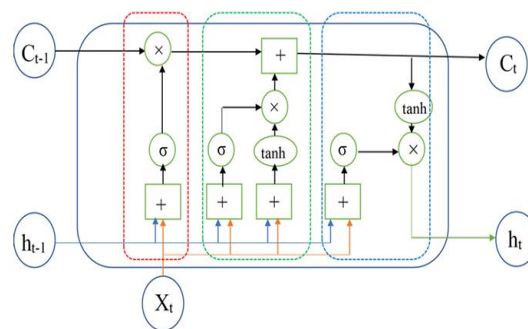


Fig. 4. Long-Short Term Memory network [1]

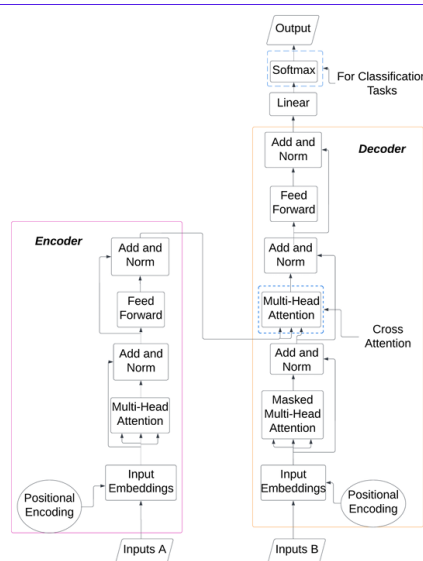


Fig. 5. Transformer architectures [1]

4.2 Water Quality Monitoring

Water quality can be analyzed with high precision through the combination of IoT sensors and Machine Learning - with models reaching 0.99 precision for both classification and regression in assessing automated water quality, as shown in Fig.6 [62]. In addition, AI and in-situ optical sensors are now being used together to identify complex contaminants in real time, such as pharmaceutical compounds or pesticide contaminants, that have historically been difficult to quantify [68].

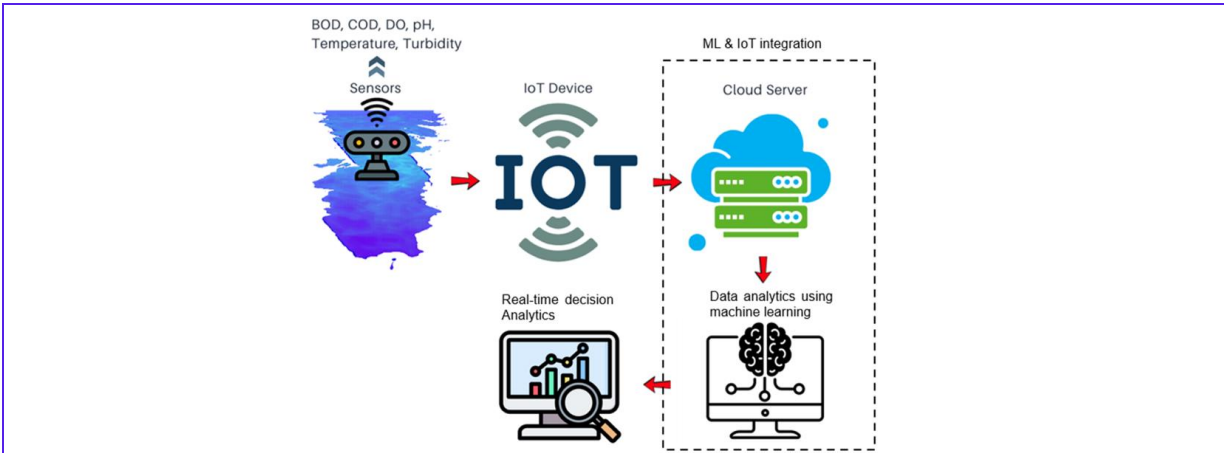


Fig. 6. IoT in water quality monitoring [62]

4.3 Smart Water Infrastructure

The HydroSense Project as shown in Fig.7, is an application of an IoT framework using dual-microcontroller technology and can be used to monitor multiple parameters including pH, dissolved oxygen and nitrogen levels. The HydroSense project's goal is to provide a scalable low-cost urban water management model [69].

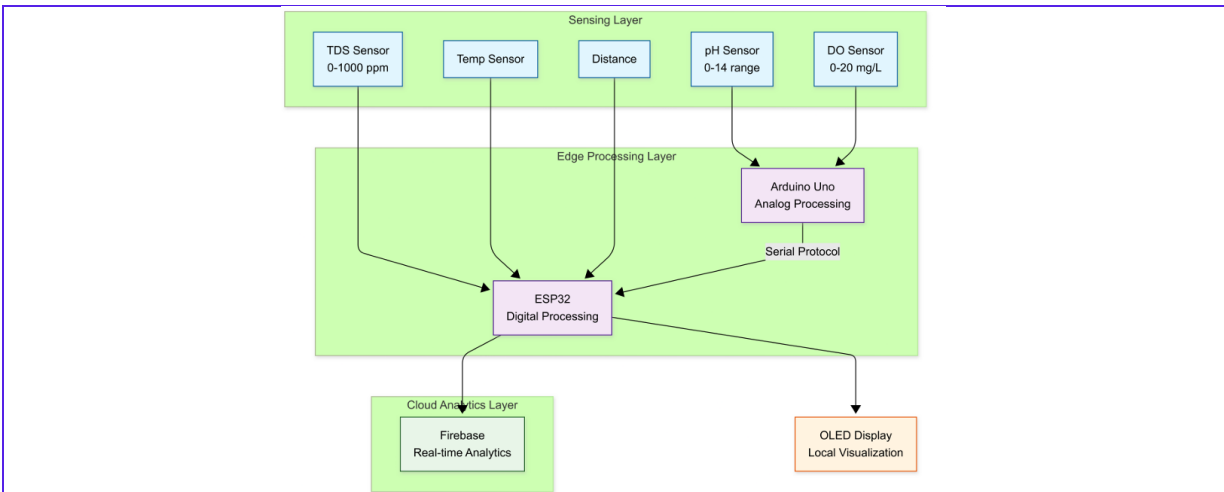


Fig. 7. HydroSense Three-Layer Distributed Architecture [69]

In this section on core applications in water resources, there is a table summarising key claims from the current literature concerning Core Applications in Water Resources, as well as specific examples of the evidence provided in support of these claims, as assessed for validity by relevant experts. See Table 6.

Table 6. The claims and evidence for core applications in water resources

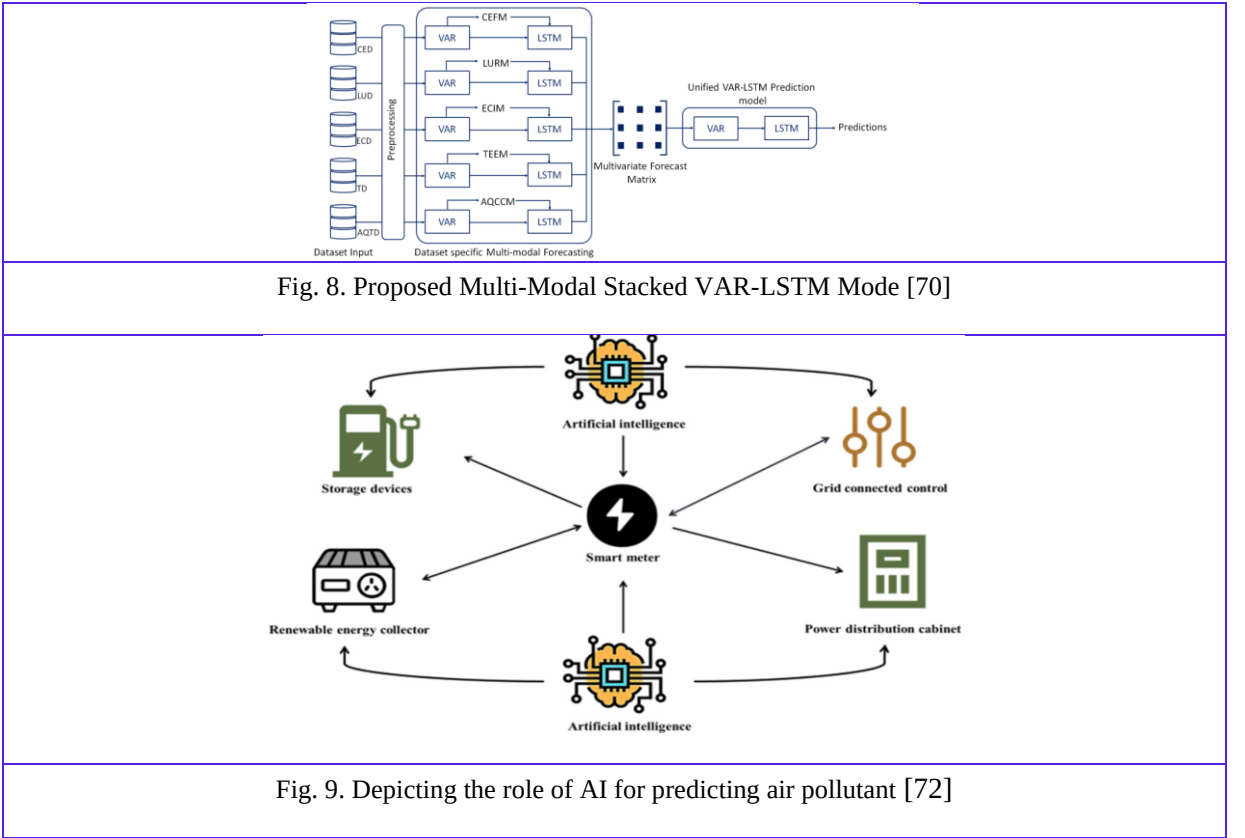
Claim	Supporting Evidence	Strength of Evidence
High-Precision Flood Forecasting	Deep learning techniques, especially Long Short-Term Memory (LSTM), perform better than traditional methods in predicting floods 3 or more days into the future in tropical regions, with Nash-Sutcliffe efficiency values exceeding 99% for flow rates[1]	 Very high
Long-Range Streamflow Prediction	Transformer architectures have the ability to effectively model historical temporal dependencies for streamflow prediction using both 1-day and 5-day forecasts and work well across many different datasets [59], [60]	 High
Real-Time Water Quality Classification	Within an IoT-enabled environment, machine learning approaches (such as Random Forest and Neural Networks) achieve accuracies exceeding 0.99 for water quality classification/assessment [62]	 Very high
Edge-Based Infrastructure Monitoring	Dual Microcontrollers IoT applications platforms (like HydroSense) offer the ability to measure and transmit pH, DO and nitrogen measurements concurrently; they will also offer local data processing, which will enable real-time monitoring and reduce cloud data latency [69].	 High
Advanced Contaminant Detection	In-situ optical sensors combined with artificial intelligence can now detect complex contaminants, such as pesticides and pharmaceuticals, in real time, which may have previously been impossible to measure [68]	 Moderate/ High
Hybrid Modeling for Nonlinear Pollutants	By incorporating wavelet transforms or metaheuristic optimizations into the AI model, the performance of the AI model can greatly enhance by modeling the nonlinear behaviours of water contaminants when compared to the performance of the AI model alone[65], [66]	 High
Adaptive Resource Management	Reinforcement Learning is crucial for the transition from passive predictive approaches to active, decision-based management of water resources	 Moderate

Table 6. The claims and evidence for core applications in water resources		
Claim	Supporting Evidence	Strength of Evidence
	[58], [67]	

5. Core Applications in Environmental Engineering

5.1 Air Quality and Climate

The usage of artificial intelligence models to help understand the connection between urbanization and carbon footprints has drastically increased, as shown in Fig.8 [70]. The Random Forest algorithm has been particularly successful in aiding researchers to assess air quality in low-resource areas, reaching a classification accuracy of 0.89 when testing daily air quality index values [71]. AI and ML methodologies have been rapidly expanding their use and capabilities to accurately provide predicted atmospheric concentrations of air pollutants (such as PM2.5, NOx and O3) through the integration of information derived from meteorological datasets, emissions inventories and satellite observation data [72]. The prediction of carbon sequestration rates also apply ML techniques that will analyze the various soil properties, vegetation characteristics and climatic variable to assist in climate change mitigation processes. Climate impact assessments are also being completed through the use of deep learning techniques that allow researchers to downscale global climate models and subsequently predict specific local environmental changes. See Fig.9.



5.2 Waste Management and Circular Economy

Artificial Intelligence is leading the shift towards a circular economy by implementing automated sorting processes. Intelligent platforms that integrate robotics and computer vision are capable of classifying different waste types with high levels of accuracy, greater than 95%. They will lessen the need to extract raw materials from the environment by developing efficient, circular processes for reclaimed materials [56]. Utilizing robotics and computer vision, AI-based waste sorting systems can rapidly sort recycling materials and ultimately increase the amount of recyclable material collected and decrease contamination of recyclables [73]. The optimization of supply chains in a circular economy through predictive analytics utilizes ML to forecast how materials will flow through the supply chain; optimize reverse logistics; and identify opportunities for recovering resources [74]. Predictive maintenance of waste management and recycling facilities uses AI to plan for preventative maintenance, minimize equipment downtime, and extend the useful life of facilities/equipment. See Fig.10.

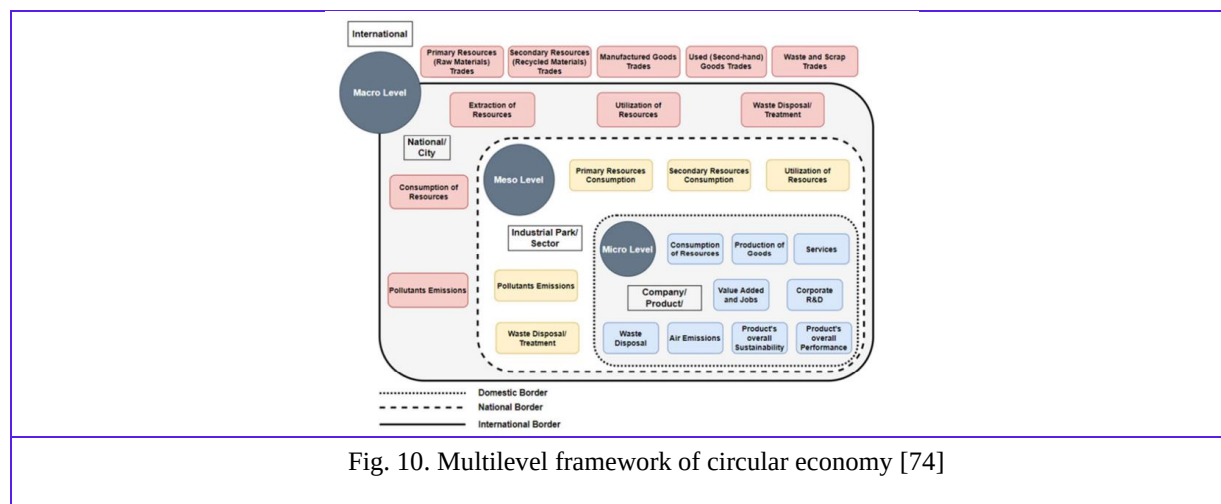


Fig. 10. Multilevel framework of circular economy [74]

5.3 Ecological Monitoring

AI enables the rapid assessment of pollutants and may allow for quicker responses to incidents which exceed normal pollution levels in the water. AI solutions such as YOLO and Mask R-CNN provide very high rates of accuracy for predicting and detecting oil spills and marine debris in difficult-to-analyze marine environments [75]. By using big data analytics and machine learning (ML) on multiple data sources including audio recordings, motion-activated cameras (known as camera traps), and genetic material (eDNA), machine-assisted quantitative measurements of both species and ecosystem health can be obtained at a broader spatial scale. Satellite imagery combined with ML techniques provides near-real-time observations of land use/cover changes that assist with conservation efforts and policy compliance through tracking and monitoring deforestation. Machine-assisted decision support tools are utilized in restoring wetlands by providing improved methods for determining the restoration approach based on ecological variables, hydrological variables and socio-economic variables [76].

5.4 Sustainable Manufacturing

AI is a critical part of the manufacturing process. AI's primary function is to maximize resource utilization, minimize waste generation and reduce the overall negative environmental impact of production operations. Utilizing AI and ML technologies in products and processes through the use of life cycle assessments (LCAs) will ultimately assist designers with making sustainable design selections. The integration of AI into energy management systems will enable companies to efficiently utilize energy while reducing their carbon footprint [77]. See Fig.11.

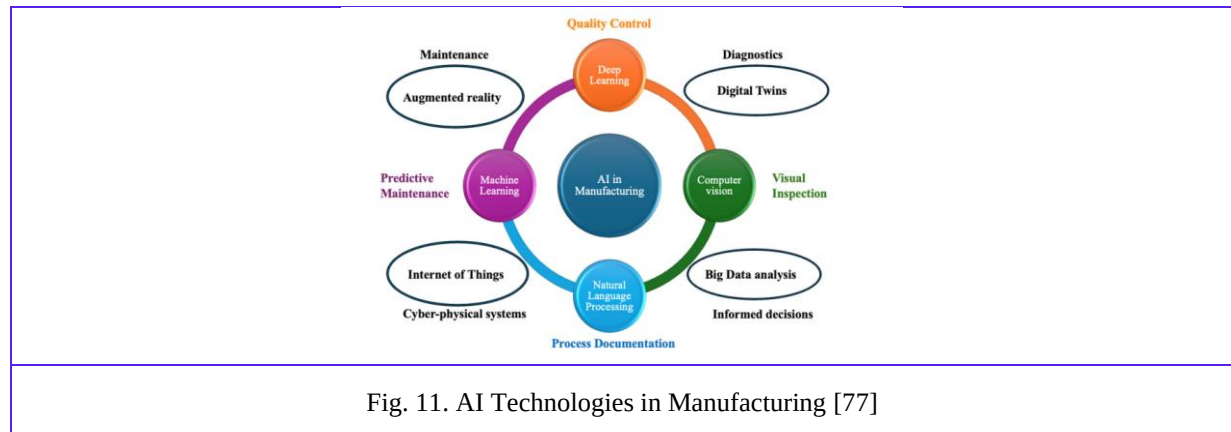


Fig. 11. AI Technologies in Manufacturing [77]

Based on the literature, here is Table 7 with claims, supporting evidence, and strength of evidence for core applications in Environmental Engineering.

Table 7. The claims and evidence for core applications in environmental engineering.		
Claim	Supporting Evidence	Strength of Evidence
Recycling efficiency and material recovery are greatly improved when artificial intelligence assists with sorting.	The development of AI-enabled image recognition allows for the automated identification and separation of waste, reducing the potential loss of valuable materials in a waste stream. A recent pilot project is being run by Unilever and Alibaba to trial an AI-sorting machine that can segregate types of plastic and potentially allow for high-volume circular plastic recycling across China [78].	 High
Increased value recovery of materials from e-waste through robotic disassembly.	Apple's Daisy robot has the ability to disassemble 200 iPhones per hour, which allows for disassembly of components and recovery of materials at a higher-quality level than traditional recycling facilities would provide [78]. This creates a greater value recovery of materials and provides markets for secondary products.	 High
Artificial intelligence is a leading enabler of circular economy business model innovation.	Artificial intelligence has the potential to assist in designing for sustainability and robustness in product development, facilitate new circular business models to support circularity, and complement the broader infrastructures required to scale the circular economy. The CE concept is built on the principles of reduce, reuse and recycle to reduce waste [78].	 Moderate
Waste handling processes in the construction and demolition	Machine learning technology provides solutions for optimizing	 Moderate

Table 7. The claims and evidence for core applications in environmental engineering.		
Claim	Supporting Evidence	Strength of Evidence
industries can be optimized through machine learning.	waste handling processes through estimating recycling rates, predicting future construction waste and allowing for the classification and sorting of waste materials for improved recycling efficiency [79]	
Artificial intelligence and machine learning applications have the potential to revolutionize the way we manage e-waste.	An example of how artificial intelligence and machine learning can be used as an innovative solution to problems in e-waste disposal is through their ability to address the key bottlenecks associated with e-waste handling, such as providing precise identification of materials, automating the disassembly of e-waste, improving recycling rates, and predicting logistics of transporting e-waste to processing facilities [79]	 High
The use of machine learning algorithms with multi-source remote sensing data will enable detailed monitoring and restoration of wetlands.	The integration of multiple remote sensing (RS) data types and associated machine learning algorithms represents an exciting opportunity to advance science in support of management decisions. This meta-analysis presents possible future research directions, as well as a baseline framework to facilitate further scientific research utilizing state-of-the-art machine learning tools for processing RS data[78] .	 High
Automatic detection and identification of wildlife using deep learning frameworks can assist in conservation.	"Tidzam" is a deep learning framework designed to detect, identify and geolocate wildlife within wetland restoration areas. With recent advancements in machine learning, it will allow for rapid development of large-scale monitoring systems to assess conservation outcomes [80].	 Moderate
Multi-temporal machine learning mapping improves monitoring of wetland vegetation.	Multi-temporal high-resolution mapping of marsh vegetation using UAS remote sensing and machine learning has demonstrated that inter-annual variability in marsh vegetation occurs in non-linear fashion, therefore, long-term monitoring is necessary for understanding marsh dynamics accurately, thus improving restoration practices [81]	 High
Artificial intelligence can predict carbon sequestration rates associated with forests.	Artificial intelligence and machine learning are used to better understand the dynamics of carbon	 High

Table 7. The claims and evidence for core applications in environmental engineering.		
Claim	Supporting Evidence	Strength of Evidence
	sequestration in forests through analysis of tree species, soil composition and climate conditions; thus, machine learning based models can help predict how ultimately land use changes impact carbon sequestered [82]	
Artificial intelligence-based systems provide the ability to monitor large amount of forest carbon.	Remote sensing technologies (i.e., satellite imagery and LiDAR data), combined with machine learning techniques are used to provide large-scale assessments of the stocks and trends of forests' carbon; artificial intelligence-based systems can then analyze the large datasets in real-time to allow researchers to monitor changes in carbon levels and predict future carbon sequestration [83].	 High
AI aids in defining the characteristics of a sustainable carbon-neutral economy.	AI uses current patterns and data to predict how much CO ₂ will be emitted over time as well as measure how much CO ₂ has already been actively removed due to sequestration [84].	 High
AI improves carbon sequestration and storage effectiveness and efficiency.	AI will improve the effectiveness and efficiency of carbon sequestration and storage by determining which geological formations are suitable for storing CO ₂ , evaluating its future behaviour when it is injected, optimising injection techniques, monitoring storage locations, and developing novel carbon sequestration approaches [85].	 Moderate
AI optimises natural systems to help adapt to climate change.	AI can forecast changes in the amount of land occupied by important forests and how these shifts impact the ecosystem services they provide, including carbon sequestration. By optimising natural systems such as the water cycle (hydrology), natural runoff patterns, and rates associated with percolation and evaporation, we will have a benchmark that indicates ideal circumstances [86]	 Moderate/1

6. Discussion: Challenges and Limitations

Even though AI and ML have made significant progress in deploying these technologies within the sectors of water resource management and environmental engineering, there are still many important obstacles preventing their use at larger scales and making them more dependable and sustainable. These

obstacles fall into five different areas: data, modeling, computing, institutions, and ethics, as recently reported by systematic literature reviews of AI and ML.

6.1 Data Scarcity and Quality

Most datasets regarding the environment do not provide extensive coverage across all times or areas nor do they always have correct measurements. Therefore, there are two problems created by ungauged basins; one is that there is no historical data available for model training, and the second is that the black box of deep learning describes processes which are difficult to explain from an expert/policy standpoint. In addition, there are many issues with data quality including, drift in sensors; missing values; and inconsistently measured physical processes result in creating additional difficulties in developing and validating models [21].

6.2 Model Generalization

Machine Learning (ML) models created using the data of a specific geographic or climatic zone often will not generalize well to another. As a result, the incompatibility of these ML models to existing conditions hinders the broader use of AI technology and necessitates the construction of region-focused models. Additionally, changing climate creates a new level of non-stationarity within environmental systems in which historical data is less informative of future environmental conditions and violates the logic that past trends will continue into future[23].

6.3 Interpretability

Environmental management is facing an urgent need for Explainable AI (XAI) because it requires transparency in decision-making - this need is apparent to water managers, policymakers, and all stakeholders who rely upon the model to provide them with predictions and influence their actions based upon these predictions. Current methods of XAI in environmental applications are still developing; therefore, they must find a balance between being able to interpret the results while providing valid predictive performance [22].

6.4 Computational Costs

Training large-scale AI models will require more computational resources/energy consumption, which creates potential threats to sustainability. Therefore, we need to consider the environmental footprint when we train AI systems, especially when we are working with limited resources. Also, because most operational systems currently require real-time inference, there needs to be an efficient way to build and deploy AI models [87].

6.5 Ethical Considerations

One area AI can pose a threat is by reinforcing/ amplifying existing bias in its training data, which will then likely impact how the water is distributed equitably or lack thereof; and could create environmental justice issues. Creating standard ethical guidelines for AI use in environmental applications will help address a number of risk factors, including privacy, accountability, and equality [78].

Based on the literature, here is Table 8 with claims, supporting evidence, and strength of evidence for challenges and limitations for Environmental Engineering.

Table 8. The claims and evidence for challenges and limitations in environmental engineering.		
Claim	Evidence	Strength of Evidence
Environmental AI is hampered by constrained dataset sizes.	Many datasets include only ~250 years of environmental data, making	 High

	it difficult to make accurate predictions about future environments using historical data [88].	
Historical data are being rendered less useful for predicting the effects of climate change upon future environments because the present trends condition the prediction process on historical data.	New events showing unpredictable significance (ozone depletion) demonstrate that the past does not always provide guidance for future events [88].	 Moderate

6.6 Regional Data Gaps and the Case of the Middle East

One notable challenge that is under-appreciated in AI/ML water resources literature is the drastic under-representation of arid and developing world areas. The overwhelming majority of AI/ML studies achieving high performance use datasets from well-instrumented basins located in Europe, North America, or East Asia (countries that are home to dense monitoring networks and decades of continuous records). Countries facing acute water security challenges, such as Iraq with its transboundary river depletion, salinization and the intensifying drought, are drastically under-represented in the global AI/ML literature [3].

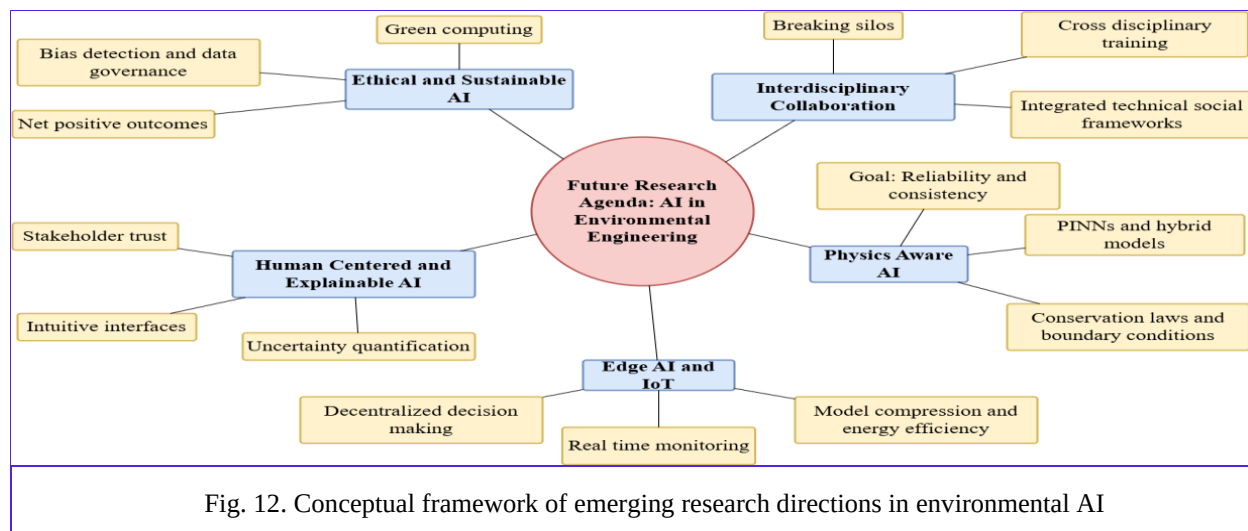
In a lot of ways geo-bias limits the direct application of published performance benchmarks for Iraq or the Middle East. Future studies about hydrology in Iraq should priorities open access data from the Tigris and Euphrates river systems, as well as Shatt Al Arab. Future research can also use federated or physics-based learning algorithms that can perform adequately with limited locally collected data.

7. Future Research Agenda

As the AI in Environmental and Water Engineering research agenda transitions from basic predictive modelling to advanced models that integrate physics (see Fig.12), the direction will be defined by new ways to apply high stake's reliability, integrated energy development and integration via energy sourced by Artificial Intelligence as following:

- 1- **Physics-Aware AI:** Integrating physical laws and domain expertise in ML architecture is one of the most important avenues of research. Physically-informed Neural Networks and hybrid models that incorporate both mechanistic and data-driven learning approaches have the potential to improve the reliability of models, enhance the ability of models to extrapolate and better maintain fidelity to the laws of physics. Research will identify efficient techniques for embedding conservation laws, boundary conditions and process knowledge into ML frameworks [89].
- 2- **Edge AI and IoT:** By embedding AI directly into low-power sensors and edge computing platforms, it is feasible to provide real-time environmental monitoring in remote locations without relying on cloud connectivity. The advantage of such an approach is that it can reduce latency, require less bandwidth and lower energy usage while providing for a decentralized decision-making system. Research will focus on developing solutions to address challenges surrounding model compression, energy efficiency and robustness in extreme environmental conditions [22].
- 3- **Human-Centered AI:** Achieving equally effective and equitable water management requires the use of participatory decision-support systems in which stakeholders are actively involved in the model creation and interpretation process. Research should include the development of user-friendly interfaces, visualization tools and collaborative frameworks that help bridge AI capabilities and stakeholder needs and/or expectations. Co-design approaches that marry the local expertise of stakeholders with AI-derived predictions will increase model usability and acceptance [78].
- 4- **Explainable AI:** XAI Methods That Are specifically advanced for the environment, expanding externally AI technologies for use in environmental decision-making is fundamental to creating both trust in and informed choices about technology. Research into XAI would create interpretable models that provide understanding via the application of physical and theoretical explanations,

- demonstration of quantifiable uncertainty, and the capacity for scenario analysis. XAI Frameworks, however, are required to develop for disparate areas (e.g., scientist), adjacent disciplines (e.g., policy-makers) and end-users (e.g., community stakeholders) [22].
- 5- **Ethical AI Frameworks:** A comprehensive framework for ethical ai in water resources and environmental engineering. There is an urgent need for the creation of comprehensive ethical frameworks to govern the use of AI technologies in water resources and environmental engineering. Ethical frameworks must address the governance of the data used to create algorithms; provide transparency into algorithmic processes; provide accountability mechanisms; and include considerations for achieving distributive equity in the use of AI technologies. Research is required to develop best practices for detecting and mitigating bias, measurement of fairness, and participatory governance structures for the use of AI technologies [78], [90].
 - 6- **Sustainable AI:** Environmentally Sustainable AI Approaches The continued evolution of AI will depend on research and development of environmentally sustainable AI solutions that will achieve their intended results with the least amount of environmental impact (i.e. computational footprint), while still maintaining the technical requirements for performance. Research must explore the following: to develop efficient model architectures; develop green computer-based solutions; and evaluate the lifecycle of AI technologies to help measure any environmental benefits produced by the AI technologies against the resource consumption cost to produce them.
 - 7- **Interdisciplinary Collaboration:** To achieve future advancement, there is need for greater cooperation among computer scientists; hydrologists; environmental engineers; social scientists; and public officials. Through interdisciplinary research groups it will be possible to create more complete solutions to the technical, social, and institutional facets of artificial intelligence (AI) usage within water resources and environmental management. The creation of educational programs needs to focus on preparing the new generation of scientists by providing the skills necessary for collaboration across disciplines [91].



Based on the literature, here is Table 9 with claims, supporting evidence, and strength of evidence for the AI in environmental and water engineering research agenda.

Table 9. The claims and evidence for the AI in environmental and water engineering research agenda.		
Claim	Evidence	Strength of Evidence
Policies need explainable AI, as it will provide a basis for trust	Through increased transparency, XAI provides transformational changes regarding sustainability driven by Data [22]	High
Guidance on developing ethical guidelines for AI for circular	Guidelines are needed to reduce risk systems arising from AI	Moderate

economy is absent

resource transition [78]

An established research agenda is required to establish AI / ML approaches suited to the hydroclimatic environment of the Middle East. Research priorities include: (i) developing open, standard datasets for hydrometry and water quality data so that we have comparable datasets from Iraq's river systems; (ii) transferring learning to create models with training datasets from regions with large numbers of measuring stations (termed data-rich basins) for regions with little or no hydrological data (termed ungauged or data-scarce watersheds); (iii) creating systems for advanced risk warning to monitor at risk of flooding and drought in the Tigris – Euphrates basin where predictive models show an increase in hydrological extremes due to climate change; and (iv) developing policy tools to incorporate AI into Iraq's national water management policy framework in conjunction with the Iraqi Ministry of Water Resources.

8. Conclusions

AI (Artificial Intelligence) and ML (Machine Learning) have provided new capabilities in water resources / environmental engineering and can assist in solving some of the world's complex problems. The movement away from traditional mechanical models to more sophisticated architectures such as Transformers and LSTMs has led to significant improvement in the ability to produce accurate hydrological predictions and to monitor hydrology in real-time. Reinforcement Learning has also enabled optimisation of reservoir operation, decreasing irrigation water use, and detecting previously undetectable contaminants.

However, deploying AI/ML technology on a wider application scale has a number of technical and ethical challenges; due to the "black box" nature of many AI models there is an interpretability gap between the model output and stakeholders' ability to trust that the machine has made the correct automated decisions for high-risk environmental situations. In addition, there is no standard method for obtaining data (i.e., there are no standards for digitising and acquiring data from equipment) and there is little availability of open-source code, which makes independent verification of research findings and reproducibility difficult.

Hybrid models that integrate the laws of nature through machine learning need to be developed as part of any future research initiative in order to eliminate some of the challenges that have been faced by engineers today. In addition, the development of AI guidelines to protect socially sensitive information when using data from sensors and reduce the carbon footprint associated with creating large scale AI models need to be developed and implemented. By emphasising an open culture surrounding data, as well as an emphasis on "Physics-Informed", the engineering profession can create sustainable, transparent and efficient systems to manage water and the environment with respect to AI.

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