Journal of Cleaner Production xxx (xxxx) 140715

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Review

Applications of machine learning to water resources management: A review of present status and future opportunities

Ashraf A. Ahmed [a,**], Sakina Sayed [a], Antoifi Abdoulhalik [a], Salissou Moutari [b], Lukumon Oyedele [c]

[a] Department of Civil and Environmental Engineering, Brunel University London, Kingston Lane, Uxbridge, UB83PH, United Kingdom
[b] Mathematical Sciences Research Centre, Queen's University Belfast, United Kingdom
[c] Bristol Business School, University of West of England, Bristol, BS16 1QY, United Kingdom

ARTICLE INFO

Handling Editor: Cecilia Maria Villas Bôas de Almeida

Keywords:
Water quality
Flooding
Wastewater treatment
AI and deep learning
Reinforcement learning
Unsupervised learning

ABSTRACT

Water is the most valuable natural resource on earth that plays a critical role in the socio-economic development of humans worldwide. Water is used for various purposes, including, but not limited to, drinking, recreation, irrigation, and hydropower production. The expected population growth at a global scale, coupled with the predicted climate change-induced impacts, warrants the need for proactive and effective management of water resources. Over the recent decades, machine learning tools have been widely applied to various water resources management-related fields and have often shown promising results. Despite the publication of several review articles on machine learning applications in water-related fields, this review paper presents for the first time a comprehensive review of machine learning techniques applied to water resources management, focusing on the most recent achievements. The study examines the potential for advanced machine learning techniques to improve decision support systems in the various sectors within the realm of water resources management, which includes groundwater management, streamflow forecasting, water distribution systems, water quality and wastewater treatment, water demand and consumption, hydropower and marine energy, water drainage systems, and flood management and defence. This study provides an overview of the state-of-the-art machine learning approaches to the water industry and how they can be used to ensure water supply sustainability, quality, and flood and drought mitigation. This review covers the most recent related studies to provide the most recent snapshot of machine learning applications in the water industry. Overall, LSTM networks have been proven to exhibit reliable performance, often outperforming ANN models, traditional machine learning models, and established physics-based models. Hybrid ML techniques have exhibited great forecasting accuracy across all water-related fields, often showing superior computational power over traditional ANNs architectures. In addition to purely data-driven models, physical-based hybrid models have also been developed to improve prediction performance. These efforts further demonstrate that Machine learning can be a powerful practical tool for water resources management. It provides insights, predictions, and optimisation capabilities to help enhance sustainable water use and management and improve socio-economic development, healthy ecosystems and human existence.

1. Introduction

Water is the most essential natural resource for human life that is used in various ways, which are keys for human socio-economic development. Water is used for drinking, bathing, recreational activities, agriculture, hydropower production, and more. Although water covers around 70% of the earth's surface, only about 2.5% is freshwater (Science Daily, 2020). Therefore, appropriate water resources management is crucial to a well-developed society. As a complex system of nature, aquifers are constantly changing. Hence, our accessibility to freshwater is continually changing, too. In its water scarcity report (2020), the United Nations estimates that by 2025, 1.8 billion people will be living in water-scarce areas, highlighting the urgent need for innovative solutions within the water sector. Engineers and decision-makers constantly look for promising methods to address climate change and its consequential impacts. As temperatures rise rapidly, more extreme weather is observed. One of the most concerning consequences is flooding, with over one billion people worldwide predicted to live in cities with a risk of catastrophic flood levels due to climate change (Rentschler and Salhab, 2020). A natural disaster, such as a devastating

** Email: ashraf.ahmed@brunel.ac.uk

https://doi.org/10.1016/j.jclepro.2024.140715
Received 23 August 2023; Received in revised form 31 December 2023; Accepted 10 January 2024
0959-6526/© 20XX

level of flooding, can cost lives, property, crop destruction and much more. The damaging effects of flooding can have a long-lasting impact on the affected area, which can be challenging to recover from (see Table 1).

On a global scale, the exploitation and consumption of water resources often need to be better managed. An important aspect of water resources management is providing solutions for optimal resource use, ensuring overexploitation does not occur, and equipping water resources managers with the appropriate decision-support tools to plan for potential shortages of effective management. Conventionally, physical models have assisted decision-makers in enabling a sustainable and optimal use of water resources. However, the relationships between hydrological, meteorological and water table levels are well known to be very complex. Additionally, these models require a larger number of data, and such data tend to be very expensive and/or scarce, particularly in developing countries.

Table 1
Summary of statistical and machine learning models as well as their associated paradigms and tasks.

Models		Paradigm	Task
Statistical models	Linear regression	Supervised learning	Regression,
	Nonlinear regression	Supervised learning	Regression
	Regularized regression models: Ridge Regression, LASSO	Supervised learning	Regression
	Generalized linear models	Supervised learning	Classification, regression
	ARIMA	Supervised learning	Regression, time series forecasting
Machine Learning models	Decision Trees	Supervised learning	Classification, regression, time series forecasting
	SVM/SVR	Supervised learning	Classification, regression
	Naïve Bayes	Supervised learning	Classification, regression, time series forecasting
	Gradient Boosted Trees, AdaBoost, XGBoost	Supervised learning	Classification, regression, time series forecasting
	Random Forest	Supervised learning	Classification, regression, time series forecasting
	K-NN	Supervised learning	Regression, time series forecasting
	Deep learning: ANN, RNN, CNN, GAN, GRU, LSTM, DBN, DCGAN	Supervised learning	Classification, regression, time series forecasting
	Autoencoders, SAE, DEA, VAE, RBM, DBM	Unsupervised learning	Feature extraction, dimensionality reduction
	Clustering: k-mean, k-medoid, GMM-based clustering	Unsupervised learning	Feature extraction, dimensionality reduction
	PCA, UMAP, Isomap Embedding, NMF, Apriori	Unsupervised learning	Feature extraction, dimensionality reduction
	Filter Methods	Unsupervised learning	Feature selection, dimensionality reduction
	Label Spreading, Label Propagation, Self-Training classifier	Semi-supervised learning	Classification
	Q-Learning, MDP, SARSA, PPO, PG	Reinforcement learning	Decision-making
	Hybrid models: ARIMA-ANN, Deep Q-Learning, Deep Reinforcement Learning	Supervised learning, Reinforcement learning	Classification, regression, time series forecasting, decision-making

In recent years, Machine Learning (ML) has demonstrated its high efficiency and practicability for water resources management compared to traditional models due to its capability to handle different sources simultaneously and its lower cost and time requirements. ML has been applied to water resources management in various ways to improve the monitoring, prediction, and sustainable use of water resources. ML models are often trained on historical hydrological data for forecasting. The main hydrological data commonly used as input features include discharge, rainfall, water table level, temperature, evapotranspiration, land use, and pumping rates. Preference has recently been given to data-driven models over physically based or conceptual forecasting models, which have the potential to unravel the non-linear input-output relationship and produce reliable predictions of physical systems, even without prior knowledge of the underlying physical relationships and the catchment information.

There are numerous examples of how ML can be applied to water resources management. For example, ML can analyse historical usage data in a water distribution system, provide optimum water allocation, predict future demand, and help detect system leaks (e.g. Shahra et al., 2019). With the availability of historical data on groundwater levels, ML has been widely used for future predictions of water level dynamics, which helps in the management of groundwater reservoirs (e.g. Pathak et al., 2021; Ghosh et al., 2022; Kochhar et al., 2021; Teimoori et al., 2023). ML can also be used for streamflow forecasting (e.g. Cheng et al., 2020; Mehedi et al., 2022; Dehghani et al., 2023; Akbarian et al., 2023).

There is increasing pressure on irrigation water demand for agriculture use, which is expected to double by 2050 (The Food and Agriculture Organization of the United Nations, 2017), with only limited resources. ML has been extensively used to narrow this gap and to develop smart irrigation practices (e.g. Chen et al., 2021; He et al., 2022). Another example where ML has proved successful is the water quality prediction. This has been crucial given that water pollution has worsened significantly in most rivers in Africa, Asia, and Latin America (United Nations Environment Programme, 2016). This has prompted many studies focusing on the applications of ML to estimate and predict water quality (e.g. Qu et al., 2020; Zhou, 2020).

This study presents an overview of the recent water resources-related studies that implemented ML algorithms, with the main aim being to answer the following research question: which ML algorithms have been used in water resource management in recent years, and what were the most effective approaches adopted for forecasting application? This provides the most up-to-date and relevant information pertaining to the application of ML to the water sector, thereby highlighting its relevance and potential in practical application. Most of the research studies covered in this review extend from the time we initiated it until October 2023.

Nomenclature	
Abbreviations	*Significations*
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
Bi-LSTM	Bidirectional-LSTM
CNN	Convolutional Neural Network
Conv LSTM	Convolutional LSTM
DI	Data Integration
ELM	Extreme Learning Machine
En-De	Encoder-Decoder
GA	Genetic Algorithm
GB	Gradient Boosting
GBRT	Gradient Boosted Regression Trees
GHM	Global Hydrological Model
GloFAS	Global Flood Awareness System
GMDH	Group Method of Data Handling
GNN	Graph Neural Network

Nomenclature

Abbreviations	*Significations*
GRU	Gated Recurrent Unit
GWO	Grey Wolf Optimisation
KGE	Kling-Gupta Efficiency
LASSO	Least Absolute Shrinkage and Selection Operator
LR	Linear Regression
LSSVM	Least-squares support-vector machines
LSTM	Long Short-Term Memory
MLP	Multilayer Perceptron
MLR	Multivariate Linear Regression
NARX	Nonlinear AutoRegressive network with eXogenous inputs
NSE	Nash–Sutcliffe efficiency
PCA	Principle Component Analysis
PCC	Pearson Correlation Coefficient
PSO	Particle Swarm Optimisation
R2	Coefficient of Determination
RF	Random Forest
RNN	Recurrent Neural Network
SAC-SMA	Sacramento Soil Moisture Accounting Model
SAE	Stacked Auto Encoder
seq2seq	sequence-to-sequence
SVM	Support Vector Machine
SVR	Support Vector Regression
SWAT	Soil & Water Assessment Tool
WT	Wavelet Transform

2. Machine learning methods

Various statistical and Machine Learning (ML) techniques have found significant applications in water resource management for prediction purposes, ranging from pure forecasting to estimating certain parameters of optimisation models (table 1). Statistical models provide mathematical representations of observed data, which are used for prediction purposes. They are generally based on variants of regression models, which include simple linear regression, multiple linear regression, generalized linear models, nonlinear regression, and autoregressive integrated moving average models (ARIMA) (Bovas and Johannes, 1983; Agresti, 2011; Agresti and Franklin, 2011), regularized regression models - such as Ridge regression (Hoerl and Kennard, 1970), Least Absolute Shrinking and Selection Operator (LASSO) (Tibshirani, 1996) - as well as logistic regression models (Agresti, 2011). The latter are used for classification.

ML can be cast as either (i) supervised learning, (ii) unsupervised learning, (iii) semi-supervised learning or (iv) reinforcement learning.

2.1. Supervised learning

Supervised learning techniques are used to devise a functional mapping between input variables and output variable(s) which have proven to be efficient for prediction tasks. Depending on the type of the dependent variable(s), a supervised learning technique is categorised as either a classification model (for a nominal dependent variable) or a regression model (for a continuous dependent variable). Therefore, statistical models can be viewed as supervised learning techniques. Classification models for ML include Decision Trees classifiers (Breiman et al., 1984; Quinlan, 1986), Support Vector Machines (SVM) classifiers (Cortes and Vapnik, 1995; Steinwart and Christmann, 2008), Naïve Bayes classifiers (Domingos and Pazzani, 1997), Adaptive Boosting (AdaBoost) classifiers (Freund and Schapire, 1995), Gradient Boosted Trees classifiers (Friedman, 2001; Hastie et al., 2009), Extreme Gradient Boosting (XGBoost) classifiers (Chen and Guestrin, 2016), Random Forest classifiers (Breiman, 2001), Linear Discriminant Analysis (LDA) (Friedman, 1989). Regression models include the regression variants of the aforementioned classifiers, namely Decision Trees regressors (Breiman et al., 1984), Support Vector regressors (SVR) (Drucker et al., 1997), Naïve Bayes regressors (Frank et al., 2000), AdaBoost regressors (Freund and Schapire, 1995), Gradient Boosted Trees regressors (Friedman, 2001; Hastie et al., 2009), XGBoost regressors (Chen and Guestrin, 2016), Random Forest regressors (Breiman, 2001), as well as K-Nearest Neighbour (KNN) regressors (Cover and Hart, 1967).

Deep learning (Le Cun et al., 2015; Schmidhuber, 2015) is a class of supervised learning suitable for both classification and regression tasks, which includes classical Artificial Neural Networks (ANN) (Amari, 1972; Hopfield, 1982), Convolutional Neural Networks (CNN) (Le Cun et al., 1990), Recurrent Neural Networks (RNN) (Hopfield, 1982), Generative Adversarial Networks (GAN) (Goodfellow et al., 2014), Gated Recurrent Unit (GRU) (Cho et al., 2014), Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997), Deep Belief Networks (DBN) (Hinton, 2009), Deep Convolutional Generative Adversarial Networks (DCGAN) (Radford et al., 2015).

2.2. Unsupervised learning

Unsupervised learning techniques are used to discover patterns or relationships within labelled data. These machine learning techniques can be classified as either:

- feature extraction techniques, including Hierarchical and Partitional Clustering (e.g., K-means and k-medoid) (MacQueen, 1967; Hartigan and Wong, 1979; Kaufman and Rousseeuw, 1990), Gaussian Mixture Model (GMM)-based Clustering (Maugis et al., 2009), Principal Component Analysis (PCA) (Jolliffe, 2002), Uniform Manifold Approximation and Projection (UMAP) (Ghojogh et al., 2021), Isomap Embedding (Tenenbaum et al., 2000), Non-negative Matrix Factorization (NMF) (Lee and Seung, 2001), Association Rules (e.g. Apriori algorithm, (Agrawal and Srikant, 1994)), or
- feature selection techniques, which revolve around Filter Methods based on mutual information (Pudjihartono et al., 2022).

Variants of Deep learning (Le Cun et al., 2015) models used for unsupervised learning are Auto-Encoders (Kramer, 1991), which include Sparse Auto-Encoder (SAE) (Frey and Makhzani, 2013), Denoising Auto-Encoder (DAE) (Vincent and Larochelle, 2010), Variational Auto-Encoder (VAE) (Welling and Kingma, 2019) and Restricted Boltzman Machines (RBM) (Sherrington and Kirkpatrick, 1975), and Deep Boltzman Machines (DBM) (Salakhutdinov and Hinton, 2009).

2.3. Semi-supervised learning

Semi-supervised learning (Chapelle et al., 2006; van Engelen and Hoos, 2020) combines both supervising and unsupervised learning framework, namely when the data available consist of both unlabelled and labelled data, with the sample of unlabelled data generally outweighing the one for labelled data. Semi-supervised learning techniques include Label Spreading (Zhu and Goldberg, 2009), Label Propagation (Zhu and Ghahramani, 2002), and Self-Training classifier (Triguero et al., 2015).

2.4. Reinforcement Learning.

Reinforcement Learning (RL) (Kaelbling et al., 1996) is a framework based on an agent's behaviour with a defined environment where some feedback from previous actions are used to adjust optimally the subsequent actions. RL techniques include Q-Learning (Watkins, 1992), Markov Decision Process (MDP) (Wrobel, 1984), State-Action-Reward-State-Action (SARSA) (Rummery and Niranjan, 1994), Proximal Policy Optimisation (PPO) (Schulman, 2017), and Policy Gradient (PG) (Sutton et al., 2000).

Sometimes, different ML techniques and statistical models are combined to improve the predictive accuracy. Such hybrid approaches include the combination of RL with Deep Learning (e.g., Deep Reinforcement Learning, Deep Q-Learning) (Mnih et al., 2015), and the combination of ANNs with ARIMA (Zhang, 2003).

This study aims to provide a comprehensive overview of the applications of machine learning in water resources management related fields, including groundwater management, water distribution systems, water quality and wastewater treatment, water demand and consumption, hydropower and marine energy, irrigation and agriculture, water drainage systems, and flood management and defence. The following sections provide an overview of the recent water resource-related research studies where ML algorithms were implemented. (Fig. 1).

3. Review methodology

This review involved establishing a systematic literature search on the water industry. ScienceDirect and Scopus were mainly used as the database. The search also mainly focused on journal articles. Two sets of keywords were used, where one set included the machine learning elements, and the other set included elements related to the water industry. Those relating to the former included keywords such as ‘machine learning’, ‘deep learning’, ‘neural networks’, ‘LSTM’, ‘long short-term memory’, ‘random forest’, ‘genetic algorithm’, ‘support vector machine’, ‘extreme learning machine’, and ‘extreme gradient boosting’. Those relating to the latter included keywords such as ‘groundwater’, ‘water distribution systems’, ‘water quality’, ‘wastewater treatment’, ‘water demand’, ‘water consumption’, ‘hydropower’, ‘marine energy’, ‘irrigation’, ‘agriculture’, ‘river basin management’, ‘water drainage systems’, ‘flood management’, and ‘water retaining structure’. The searches were limited to mainly include journal publications. While the search mainly focused on the articles published in the past ten years, some older articles were cited.

4. Groundwater management

Groundwater resources are large natural reservoir located within the ground. Arid areas often rely on groundwater resources for water supply, irrigation and industrial activities. (Pathak et al., 2021; Ghosh et al., 2022). Half of drinking water is supplied by groundwater, and irrigation accounts for nearly 43% (Rajeevan and Mishra, 2020). However, natural and human factors have put groundwater resources under tremendous pressure. The main detrimental factors impacting groundwater quantity and quality include climate change, population growth, and agricultural demands. Most groundwater-related studies where ML was applied focus on groundwater level (GWL) forecasting. Understanding groundwater flow dynamics is essential to assess the potential availability and scarcity of water. Hence, a sustainable management of the available groundwater resources in arid and semi-arid regions is contingent of an accurate and reliable prediction of GWL, which directly reflects groundwater availability and provides relevant cues on its hydrodynamics. However, characterising groundwater dynamics is a difficult task since the occurrence and availability present spatial and temporal variations, which depend on several factors, including, but not limited to, slope, geology, rainfall, and soil type.

A large number of studies have demonstrated the usefulness of data-driven models for GWL application, especially in data-scarce context and/or complex aquifer systems. Conventional approaches applied to GWL have often involved the use of multivariate linear regression models (MLR), autoregressive integrated moving average (ARIMA) model, and seasonal autoregressive moving average (SARIMA) (e.g., Rahaman et al., 2019), which are generally considered as linear fitting models. Future predictions could be derived using the SARIMA model along with the input and output of groundwater data (Kochhar et al., 2021). Teimoori et al. (2023) demonstrated that K-means clustering and relevance vector machine (RVM) could identify the optimal number and location of monitoring wells and thus help design efficient groundwater level monitoring networks.

Traditional ML models have also yielded acceptable GWL prediction performance. Rohde et al. (2021) use the ensemble-based Random Forest model and satellite-based remote sensing for long-term GWL prediction in California, USA. GWL was forecasted within all groundwater-dependent ecosystems across the state. They demonstrated that their results could be used to help groundwater data gaps filling and improve sustainable groundwater management policy in California even in the absence of groundwater monitoring well data. Liu et al. (2022) also implemented Random Forest and found it very effective in predicting GWL in the lower Tarim River. They demonstrated that RF was superior to other models in one-step-ahead predictions of groundwater depth in the space-time domain. Sharafati et al. (2020) assessed the performance pattern of the Gradient Boosting Regression (GBR) model to predict the monthly GWL with short- and long-lead times over the Rafsanjan aquifer. This study demonstrated the performance of GBR in predicting GWL. Regions with higher water depth and abstraction rates yielded

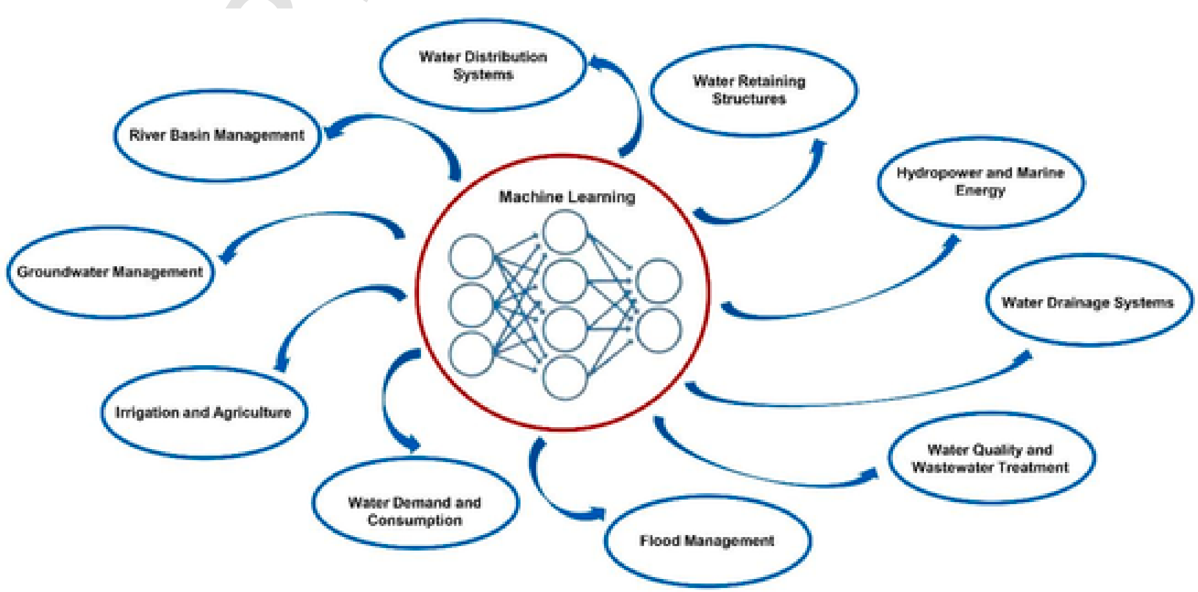

Fig. 1. The different water resource management related applications covered in this review.

better prediction performance. Hikouei et al. (2023) found that XGBoost exhibited good performance, reduced prediction uncertainties, and could capture true features of GWL in areas near canals. Their results showed that peat surface elevation was the most important parameter amongst other parameters tested, including precipitation, distance from the canal, and evapotranspiration.

Several studies have shown that standalone deep learning models are more performant than traditional ML models but are still subjected to data characteristics that can affect their performance. The most common ML implementation is the use of artificial neural networks, which have been used to predict the dynamics of GWL in numerous studies. Ahmadi et al. (2022) showed that feed-forward ANN was very effective in groundwater characteristics quantitatively with good accuracy. Taormina et al. (2012) compared the ability of feed-forward neural network (FFANN) in forecasting GWL to regression and statistical models. Mohanty et al. (2015) and Li et al., 2018 also employed neural networks to predict GWL and found positive results.

Another common application of ML in GWL forecasting is using deep learning models such as the LSTM, Gated Recurrent Unit (GRU) and the Recurrent Neural Network (RNN). Cai et al. (2021) evidenced the superiority of the GRU model in regions with higher precipitation, higher average temperatures, lower snowfall fraction, more extreme climate events, and more frequent baseflow interactions. Regarding input features for the model, precipitation and streamflow data were found to be the most influential ones for groundwater level forecasting. Gharehbaghi et al. (2022) also examined the performance of the GRU model in Northwest Iran. They used three different layer structures of GRU-based neural network models via the seq2seq module, a modern deep learning scheme. Their proposed models could predict groundwater level fluctuations in arid/semi-arid regions. Wu et al. (2023) showed that the GRU model outperformed SVM, LSTM and MLP models at most groundwater monitoring stations.

Recently, Pham et al. (2022) investigated the performance of seven machine learning models, namely random tree (RT), random forest (RF), decision stump, support vector machine (SVM), locally weighted linear regression (LWLR), as well as reduced error pruning tree (REP Tree), for the prediction of groundwater levels in a drought-prone area. This study found that the Bagging-RT and Bagging-RF models outperformed other models. Yin et al. (2021) compared the performance of machine learning and physical models in forecasting groundwater dynamics. The physically-based models included W3 and CLSM models, while the data-driven models were based on ANN, RF and LSTM models, respectively. The predicted GWLs from the LSTM model significantly perform better than those of RF and ANN models during validation and prediction periods. They quantified the importance of GRACE observations in data-driven models and found noticeable improvements in the performance metrics considered. Liu et al. (2022) found that when compared to Support Vector Machine, Generalized Regression Neural Network, Decision Tree, Convolutional Neural Network, Long Short-Term Memory and Gated Recurrent Network, Random Forest performed the best in predicting groundwater levels. They showed that RF was superior to other models in one-step-ahead predictions of groundwater depth in the space-time domain. Mahamad et al. (2023) compared six ML models, including Linear regression, Decision tree regressor, Support vector regressor, Random Forest regressor, K-nearest neighbours regressor, and Extreme gradient boost regressor. They showed that the XGB regressor was the most reliable model for future prediction, while the Decision Tree proved to be the least efficient technique for portraying the GWL dynamics. They demonstrated that changes in GWL over space and time were strongly linked to changes in rainfall and population in the study area.

Shakya et al. (2022) compared the Support Vector Regression (SVR) model, Multivariate Linear Regression (MLR) model, Decision Tree Regression (DTR) model, Random Forest Regression (RFR) model, Multivariate Polynomial Regression (MPR) model, and two deep learning algorithms, namely ANN model and ANFIS in the task of predicting GWL in an arid area in India. They demonstrated that the MPR model was excellent for GWL forecasting and found that the groundwater table was highly correlated with evapotranspiration. Sun et al. (2022) employed three common data-driven models for GWL forecasting applications, which included a back-propagation artificial neural network (BP-ANN), an autoregressive integrated moving average (ARIMA), and long short-term memory (LSTM). The prediction accuracy of the models was tested by deploying them in five zones in a Northern Plain in China, which exhibited various hydrogeological properties. Amongst the three models, the LSTM model exhibited the best performance. Mohapatra et al. (2021) compared the performance of ANFIS, DNN, and SVM to assess their capability to predict seasonal GWL in different agroecological Zones of India. They found that the DNN model was the most efficient in predicting seasonal GWL in most of these agroecological zones and would, therefore, be a reliable forecasting tool for seasonal groundwater levels in different agroecological zones of India.

Wunsch et al. (2022) investigated the impact of climate change on groundwater resources in Germany using CNN. Declining trends of GWL could be observed in most of the sites as well as spatial patterns of stronger decreases, especially in the northern and eastern parts of the country. They also observed increased variability of low GWL, which extended over long periods during the annual cycle towards the end of the century. Bai and Tahmasebi (2023) compared the performance of a graph neural network (GNN) to two baseline models - LSTM and GRU - for GWL forecasting. They demonstrated that the GNN model outperformed the other models regarding all the performance metrics considered. Also, they demonstrated that their model could still learn spatial dependencies from the data even when these were completely unknown while still obtaining similar performance. Their model also exhibited a high efficiency since it could simultaneously model GWL change for all monitoring wells in the system.

In addition to standalone ML models, recent studies have also examined the performance of hybrid-based models, which combine various ML methods to improve forecasting performance. Rahman et al. (2020) used ML models coupled with wavelet transforms and showed that wavelet-based hybrid models such as WT-XGB and WT-RF were more accurate than standalone models (non-wavelet-based), which included Extreme Gradient Boosting, Random Forests, and Support Vector Regression models. They also demonstrated that the coupling of WT further improved the performance for all ML approaches, and the improvement was more significant for a longer forecasting horizon (3 months). Wei et al. (2023) used ANN models combined with wavelet transform (WT) and phase space reconstruction (PSR) and found that the performance of the WT-PSR-ANN model was better than that of the WT-ANN model and substantially better than the standalone models in GWL forecasting. They also found that the type of mother wavelet affected the accuracy of the WT-hybrid models, which was more apparent for the WT-ANN models than for the WT-PSR-ANN model. Azizpour et al. (2021) proposed hybrid models to predict the monthly GWL in Kermanshah, Iran. The hybrid models comprised a differential evolutionary algorithm to optimise the ELM and a WT to decompose the input parameters into different time series. Their study suggested that their hybrid meta-heuristic ML could effectively predict the available water quantity in the investigated study area.

Yadav et al. (2020) demonstrated that the hybrid models (HANN and HSVM) perform better than the original models (ANN and SVM) while predicting groundwater level fluctuations. They found that prediction accuracy decreased with increasing forecasting horizons for original and hybrid models. They evidenced that groundwater decline was much higher in peri-urban areas. Van Thieu et al. (2023) proposed a novel hybrid ML model combining Augmented Artificial Ecosystem Optimisation (AAEO) algorithm with a traditional MLP network and showed that AAEO-MLP exhibited the highest performance and stability with reasonable convergence. They evidenced that the AAEO was a promising approach for optimising ML models (e.g. MLP) and should, therefore, be explored for other hydrological forecasting applications (e.g., streamflow, rainfall) to further examine its performance over commonly known methods.

Other than all purely data-driven hybrid models, physical-based hybrid models combine ML models and physics-based models to improve forecasting performance. Su et al. (2020) used deep learning algorithms combined with a range of complex numerical models and large-scale Internet of Things (IoTs) to measure groundwater levels with acceptable performance. Kayhomayoon et al. (2022) proposed a new hybrid model that combines MODFLOW simulation, clustering, and optimisation tools for GWL prediction. Specifically, they simulated GWL using the MODFLOW, clustered the study aquifer into different clusters using the k-mean method, and predicted regional GWL using ANN and ANFIS methods that were optimised by the Harris Hawks Optimisation (HHO), Whale Optimisation Algorithm (WOA), and Particle Swarm Optimisation (PSO). They evidenced that the most important variables for groundwater levels in different clusters included GWL in the previous month (produced by MODFLOW), groundwater withdrawal, precipitation, temperature, and evaporation. Patra et al. (2023) compared Global-LSTM, and Local-LSTM to examine the relevance of groundwater sequential forecasting. Their study showed that the Global (MS) model was the least performant model in forecasting applications and that LSTM was reliable in GWL forecasting. They demonstrated that the local LSTM models from the mid-fan area exhibited the best choice for regional groundwater forecasting.

Groundwater is also sensitive to pollution from various sources which is related to GWL decline, particularly in coastal areas, where the associated GWL decrease caused by excessive groundwater pumping leads to seawater intrusion, pollution and groundwater quality degradation. Nitrate contamination has also become a serious threat to coastal groundwater worldwide. Hence, the application of ML on groundwater contamination, although outside the scope of this review study, warrants further investigation.

5. Surface water management

5.1. Streamflow forecasting

Machine learning has widely been applied to river basins, specifically for short-, mid- or long-term river flow forecasting, which is a pivotal task for optimal water resource management during the era of rapid climate change. The rapid evolution of hydrological variables, e.g., precipitation, substantially impacts the temporal evolution of river flow distribution in recent days, thereby rendering prediction challenges even more complex. The high uncertainty associated with basin characteristics, hydrological processes, and climatic factors affecting river flows makes streamflow prediction challenging.

LSTM Networks have gained increasing attention in streamflow forecast, given its strong learning ability for time series data and ability to process sequential time-series data (Shen and Lawson, 2021). Numerous studies have demonstrated the superiority of LSTM in streamflow forecasting over some traditional physics-based models, including the SAC-SMA model for runoff predictions (Kratzert et al., 2018) or the CaMa Flood calibrated model for streamflow and climate data forecasting (Damavandi et al., 2019). LSTM networks have recently yielded the most promising results in the realm of river streamflow forecasting (e.g., Wegayehu and Behulu, 2022). Xu et al. (2020a, 2020b) assessed the performance of LSTM networks for 10-days average flow predictions and the daily flow predictions at Hun River and Upper Yangtze River basins, respectively. The impacts of network structures and parameters, such as the batch size and the number of LSTM cells, impacted the learning efficiency and predictive accuracy. Overall, LSTM was proven to yield good forecasting capabilities compared to traditional hydrological and data-driven models tested, which included the SWAT, Xinanjiang model (XAJ), multiple linear regression model (MLR) and back-propagation neural networks (BP).

The predictive performance of LSTM models has also been compared to a wide range of machine learning models. Cheng et al. (2020) examined and compared the performance of ANN and LSTM in long lead-time forecasting in the Nan River Basin and Ping River Basin. Their ANN and LSTM models were shown to yield reliable daily forecasts up to 20 days lead time, albeit the LSTM model outperformed the ANN model when the forecasting horizon was increased. Mehedi et al. (2022) used the LSTM neural network to forecast river discharge and demonstrated its higher performance than other neural network regression models, including for longer lead periods. Dehghani et al. (2023) compared LSTM, CNN, and Convolutional Long Short-Term Memory (ConvLSTM), in hourly streamflow prediction in two rivers in Malaysia, namely the Kelantan and Muda River basins. They showed all three deep learning methods performed with high accuracy in predicting streamflow, but LSTM outperformed CNN and ConvLSTM in small basins with well-spatial distributed rainfall stations, while it underperformed them in moderate to high streamflow and large river basin. Le et al. (2021) examined and compared the performance of six supervised machine learning models in forecasting streamflow in the Red River basin in Vietnam. These included a convolutional neural network (CNN), a feed-forward neural network (FFNN), and four LSTM-based models. They also compared two standard models, LSTM and GRU, which comprised a single hidden layer, to two more complex algorithms: the stacked LSTM (Stacked LSTM) and the Bidirectional LSTM (BiLSTM). They showed that their four LSTM-based models performed better and were more stable than the FFNN and CNN models. They also evidenced that the complexity of the Stacked LSTM and BiLSTM models did not substantially improve the prediction accuracy compared to the two standard and simple models comprising a single layer (LSTM and GRU).

Akbarian et al. (2023) examined the ability of the European Centre for Medium-Range Weather Forecasts (ECMWF) ensembles in runoff forecast application, with one-to three-months lead time in Iran. Five ML models were also used for the runoff prediction, including RF, ANN, XGBoost, SVR, and MLR, while results were compared to observations. Results showed that the ANN exhibited the best fit, followed by XGBoost and RF models, while SVR and MLR models yielded lower performance. ANN and XGBoost outperformed the other models for longer lead times, but the performance decreased with an increase in forecasting horizon. Ilhan (2023) explored a variety of ML algorithms in the estimations of one-ahead instantaneous measurement of streamflow rate in the Ergene River, including LSTM neural network, ANFIS with fuzzy c-means (FCM), ANFIS with subtractive clustering (SC), and the ANFIS with grid partition (GP). All four algorithms could successfully perform in the task of streamflow prediction.

To further improve streamflow forecasting accuracy and model efficiency, a variety of traditional ML models that belong to the supervised category have also been either used directly or combined to develop hybrid models (Granata et al., 2022; Wang et al., 2023; Akbarian et al., 2023). Granata et al. (2022) proposed a novel ensemble model composed of RF and MLP algorithms and compared its forecasting capability to a deep learning model based on bidirectional LSTM networks. The results show that the two models showed comparable performance, but the forecast horizon strongly affected the predictive accuracy. Wang et al. (2023) developed a hybrid decomposition-based multi-model and multi-parameter (DMP) ensemble streamflow forecast method. Their novel ensemble forecast method extracted the characteristic periodic term and trend term of hydrological series, improved streamflow forecasting accuracy, reduced ensemble uncertainty and expanded the ensemble size.

Hybrid models combining numerical models and ML models have also been tested to improve streamflow forecasting accuracy, especially for longer forecasting horizons. Hunt et al. (2022) tested LSTM for streamflow forecasting purposes for up to 10 days lead time at ten hydrological stations in the western US. The catchment-mean meteorological and hydrological variables from the ERA5 and Global Flood Awareness System (GloFAS)–ERA5 reanalyses were used to train the LSTM model, as well as historical streamflow data. They showed for the first time that their LSTM model could be used in a hybrid system to create a medium-range streamflow forecast outperforming established physics-based models. Chu et al. (2023) assessed the ability of novel integrated streamflow modelling method combined with the DC-LSTM model with the DC-B-LSTM model in improving the forecasting performance. Both the DC-LSTM and DC-B-LSTM models were shown to outperform the standalone LSTM models for all river basins considered. Li et al. (2022) examined a hybrid model composed of a convolutional neural network and long short-term memory network (CNN-LSTM) and evidenced its superiority over the Soil and Water Assessment Tool (SWAT) model, especially in wet seasons, due to its nonlinear learning ability.

5.2. Water demand, allocation, and irrigation

5.2.1. Water demand and consumption

Potable water can be inaccessible for many reasons, including inadequate water infrastructures, climate-based issues such as drought, and overexploitation of freshwater resources. Researchers have recently attempted to apply ML in drought forecasting, including Wang et al. (2022), who assessed the feasibility of using extreme learning machines (ELMs) to forecast hydrological droughts. They deployed support vector machine models and ELMs with approximately 144 different models, and they confirmed that ELMs could forecast the standardised hydrological drought index with high precision. Their study also demonstrated that self-adaptive differential evolution ELM could outperform all other tested models and that the wavelet hybrid positively impacted the model's performance, yielding less error in their predictions.

Global water scarcity presents an extraordinary challenge, so the United Nations prioritise it among its 17 sustainable development goals for 2030. Many regions are coming dangerously close to enclosing the gap between water demand and its sustainable limit. United Nations Water (2020) estimated that the water demand rate is more than twice the population growth rate within the last century. Arid areas are facing the worst of the water crisis. Therefore, monitoring water demand is of considerable significance for decision-makers. Water resources can be more efficiently managed if demand is accurately forecasted. This will help resolve the overexploitation of precious and limited water resources.

Forecasting water demand is a challenging problem. As such, it has been approached in various ways, ranging from linear methods (Zhou et al., 2000; Alhumoud, 2008) to nonlinear regression models (Nasseri et al., 2011; Bennett et al., 2013). However, modelling water demand could be quite complex, and not all input variables have linearity between them. Due to the complexities of the water demand data, Romano and Kapelan (2014) explored the use of deep learning for forecasting and management of smart water distribution using real-life data from a water distribution network within the United Kingdom. Perea et al. (2019) applied deep learning to a previous study by Romano and Kapelan (2014) to improve the performance of existing short-term water forecasting models in Southern Spain. Banadkooki et al. (2022) attempt to resolve conflicts related to water resources in arid basins through the exploration of intelligent algorithms: genetic algorithms (GA) and non-dominated sorting genetic algorithm (NSGA-II). The study considered environmental parameters and the integrated water management indices to determine optimal water management scenarios. The study performed a variety of trade-offs to balance economic benefit and demand management. The results showed that less water was allocated to industries with high water demand to conserve aquifers and meet water demands.

The real-life application of smart metering has become more apparent in recent years. Monitoring demand is vital for the adequate management of resources across all service sectors. Recently, neural networks have been more commonly implemented to address water demand prediction issues. While the water industry has not explored the use of deep learning for smart metering as extensively as in the energy sector (Kavousian et al., 2013), Pesantez et al. (2020) attempted to address this gap using artificial neural networks and cluster analysis to forecast the water demand at the customer level. They used smart metered data on water consumption, with no differentiation between the type of user, whether residential or non-residential. The study found that support vector regression underperformed compared to random forest and artificial neural network models despite applying optimisation methods supported by previous works (Herrera et al., 2010; Mouatadid and Adamowski, 2017; Antunes et al., 2018). As inferred previously by Herrera et al. in (2010), the random forest technique was found to be either on par with or slightly outperformed the artificial neural network model.

Salloom et al. (2021) explored the use of GRU on historic water demand data and implemented k-means, an unsupervised classification method, to enhance prediction accuracy whilst also reducing the parameters fed into the model. The model was found to significantly reduce the complexity required (six times what was archived in the most current literature at the time of the study) while maintaining the predictive accuracy rate. Salloom et al. (2022) explored using a proportional-integral-derivative (PID) control approach to boost the performance and efficiency of neural network models for water demand prediction. The PID's prediction error experienced the same level of reduction as other techniques in the study; however, the efficiency of error reduction showed superior performance compared to other techniques. This was evident by the negligible effects on the number of variables via the PID approach.

Wang et al. (2022) explored the use of principal component analysis (PCA) and backpropagation (BP) neural network in water resource demand prediction in Taiyuan, China, a city subject to severe water shortages. Compared with other models (namely PCA-ANN, ARIMA, NARX, Grey-Markov, serial regression, and LSTM), the PCA-BP model outperformed them by making highly complex variables easier to compute. The model achieved this by reducing the dimensionality of the variables and transforming them into uncorrelated composite data. However, their model was limited by limited data collection, affecting its accuracy. In addition, although the model's computation accuracy was sufficient to meet the threshold, there was still room for further development.

5.2.2. Water allocation and irrigation

Water plays a vital role in irrigation and agriculture all over the world. The Food and Agriculture Organization of the United Nations (2017), FAO, states that 70% of freshwater withdrawn globally is supplied to agriculture to sustain the ever-growing human population. Future projections on the water demand for irrigated food production will double by 2050, increasing pressure on the already limited freshwater supplies. The FAO also anticipated an increase in water withdrawal by agriculture by 2050; however, this increase is only by 10%. This small increase is attributed to improved management and practices for irrigation. Therefore, efficient water use within the irrigation and agricultural sectors is crucial to lessen the strain on water demand worldwide. Evapotranspiration is an important aspect of irrigation and agriculture, which is split into two components: evaporation and transpiration. Evaporation refers to the water evaporated over a specific area, whereas transpiration refers to the water lost through the stomata of the vegetation. As these natural processes occur simultaneously, they are difficult to disentangle. Accurate estimation of the evapotranspiration rate is a vital parameter for farmers and agricultural engineers, as it helps reduce crop water demand.

Traditional methods to address these issues include the Penman-Monteith equation, which Baille et al. (1994) used as a simplified method for the rate of evapotranspiration prediction. Other approaches found success using scintillometer and meteorological measurements applied to the FAO-PM56 model, as used by Poisson et al. (2017) study. However, the authors showed that the FAO-PM56 model had more significant uncertainties when minor variations were applied and fewer input variables were used. Deep learning techniques have been extensively used to model and forecast evapotranspiration within the agricultural sector. Feedforward backpropagation ANN outperformed multilinear regression models (MLR) for predicting wind drift and evaporation losses of sprinkler irrigation systems (Al-Ghobari et al., 2018). Various studies found that convolutional neural networks (or CNN-hybrids) were more accurate than other nonlinear regression models, such as random forest or extreme gradient boosting, for evapotranspiration forecasting (Ferreira and da Cunha, 2020a, 2020b; Lucas et al., 2020).

Elbeltagi et al. (2020) opted for a more modern approach to the problem by modelling long-term evapotranspiration dynamics using deep learning algorithms in major wheat-producing sites in Egypt. They applied deep neural networks using real-life data collected from remote sensors, which included the monthly maximum temperature, the monthly minimum temperature, and the monthly solar radiation. The model parameters were intentionally chosen to give the lowest root mean squared error, following a similar procedure presented by Maroufpoor et al. (2019a,b). He et al. (2022) successfully demonstrated the use of biological heuristic algorithms integrated with an extreme learning machine (ELM) to accurately determine the daily evapotranspiration (ETo) in the Hetao irrigation district of China. In the hybrid ELMs, the optimisers include grey wolf optimiser (GWO), moth-flame optimisation (MFO), particle swarm optimisation (PSO), and whale optimisation algorithm (WOA). The GWO was highlighted as the strongest performer of the four algorithms, obtaining the highest accuracy (R^2 = 0.945–0.955), specifically using mass transfer (Tmax, Tmin, RH, u2) combination as opposed to temperature or radiation. GWO is characterised by the avoidance of local optimisation when dealing with nonlinear and multivariate functions.

Water resources can often become contaminated by agricultural runoff. Improper agricultural practices lead to elevated levels of faecal coliforms and other pollutants, thus negatively impacting the water quality of the surrounding area. Bilali and Taleb (2020) found that artificial neural networks and other machine learning models, such as random forest, multi-linear regression and decision tree, are highly accurate at predicting irrigation water quality parameters, such as the sodium absorption ratio and the TDS dissolved in the water surface. The study found that the ANNs outperformed k-nearest neighbours and support vector regression models. H. Chen et al. (2020) found that the CNNs architecture could be developed and integrated with decision tree algorithms to aid in smart feature extraction and to establish intelligent spectroscopic modelling of agricultural water pollution.

Furthermore, ANNs have been used to forecast infiltration water volume under furrow irrigation (Mattar et al., 2015), to forecast irrigation flow (Mouatadid et al., 2019), and to forecast estimates for drip irrigation systems (Karimi et al., 2020). However, Mouatadid et al. (2019) highlighted that LSTM models were able to outperform the other models used in their study, which included an ANNs model, least squares support vector regression (LSSVR), multi-linear regression (MLR) and extreme learning machine (ELM). The LSTM was coupled with a maximal overlap discrete wavelet transform analysis and bootstrap technique. The wavelet-bootstrap-ANN and wavelet-LSTM, both with three hidden layers, displayed the most accurate forecasting capability compared to the other models used in the study.

Chen et al. (2021) explored reinforcement learning, a deep Q-learning network (DQN), to develop smart irrigation practices focusing on conserving irrigation water and time without losing paddy rice yield. DQN combines the perception ability of deep learning with decision-making ability. The study found that the DQN strategy could conserve 23 mm of irrigation water compared to conventional irrigation decisions. Drainage water was also reduced by 21 mm without a reduction in yield. Alibabaei et al.'s (2022) case study in Portugal utilised a deep reinforcement learning model to optimise irrigation requirements on the site. The model would serve as a smart irrigation scheduling system that would aid farmers in water quantity and the irrigation frequency required for the site. The model, post-training, would not require expertise to operate and, thus, would be a valuable system for farmers to use after the completion of the study. The model would also adjust the irrigation requirements based on climate change, as climate data is used in the model. The study considered ANN, LSTM, and CNN. However, the LSTM was found to be better at predicting the Q-table than the other models. The trained model decreased the water requirement by 20–30% and increased productivity by 11% compared to the fixed method.

Gorgi et al. (2023) demonstrated the predictive potential of LSTM for spatiotemporal forecasting of the quality of groundwater used for irrigation. Sodium Adsorption Ratio (SAR) was highlighted as a crucial criterion for the study. An 18-year SAR dataset based in northwest Iran was supplied to the model to forecast the irrigation water quality for the subsequent year. They found that the LSTM marked against the performance indicator RBIAS showed underestimation by the model. However, when assessed against the performance indicator GA (generalisation ability), the LSTM model exhibited more acceptable performance.

The allocation of water sourced from the Transboundary River generally involves many stakeholders in different countries that share the water resource. Water scarcity and the often-conflicting use of water resources ultimately increase tensions between riparian countries. Tension can be eased by the efficient management and allocation of transboundary water resources, which warrants the need for advanced techniques to enable the proactive and efficient planning of available water for human well-being and environmental sustainability. As an attempt to apply ML techniques for water allocation in a transboundary context, Yan et al. (2019) comprehensively evaluated the water resources of China's transboundary river basins at the basin and country levels. They assessed the performance of several ML algorithms, including random forest, gradient boosting, and stacking in the task of forecasting runoff. Their study provided valuable information on long-term averaged surface water resources by country and basin in China's transboundary river basins and high-resolution runoff coefficient and runoff maps of all the riparian countries, thereby providing valuable spatially distributed runoff information. Their study also demonstrated the satisfactory implementation of ML models for water resources assessment and their superiority over traditional linear models and two popular runoff data products (the UNH/GRDC Global Composite Runoff Fields and the Global Streamflow Characteristics Dataset) from a predictive accuracy standpoint.

6. Hydropower management, marine energy and reservoir operation

6.1. Hydropower management and marine energy

Statistics from Our World in Data (2020) showed that in 2019, global fossil fuel consumption totalled 136,761 TW-hours, reaching a new record and continuing the increasing trend observed in the past years. Fossil fuels were classified into three categories: gas, coal and oil. The data showed that most consumption was attributed to oil (53,620 TW-hours), while the least consumed fossil fuel was gas (39,292 TW-hours). This leaves global coal consumption at 43,849 TW-hours. Global efforts to struggle against climate change have been increasingly witnessed over recent years by shifting towards clean and renewable energy. According to the International Hydropower Association (2020), the 2020 Hydropower Status report showed that global clean electricity generation through hydropower achieved a new record 4306 TW-hours. This record was acknowledged as the "single greatest contribution from a renewable energy source in history". However, this record can only account for a small portion of the global fossil fuel consumption in 2019, approximately 3%. Therefore, it is essential to maximise the full potential of hydropower and marine energy by exploring new methodologies to solve current problems and increase the energy efficiency provided, particularly in some parts of the developing world where the load on the system is increasing, but hydro-turbines struggle to match the demand.

The application of ML in hydropower management and marine energy has recently met some level of success. Hammid et al. (2018) explored the use of artificial neural networks on a small hydropower plant using a Kaplan turbine at the Himreen Lake dam in Diyala, Iraq, to enhance the accuracy of forecasting the energy produced. Wang et al. (2020) developed a novel integrated approach using traditional and more modern methodologies for the production capacity prediction of a hydropower station to enhance energy efficiency. A previous study by Zhang et al. (2017) found that a backpropagation neural network model, although powerful in terms of performance, took a relatively long time to train on the input data. Although a radial basis function neural network model could outperform the backpropagation neural network (Li et al., 2018), they were both prone to the risk of local minimum convergence. To avoid this challenge, Wang et al. (2020) opted for using a simple single hidden layer feedforward neural network, defined as an extreme learning machine (ELM). The corresponding model showed a generalisable performance with a relatively quick training time.

Technological advances have made it possible to predict energy that can be gained from ocean waves. This type of renewable energy carries a higher power density than other renewable resources, such as solar or wind energy. Accurate predictions can enhance energy efficiency to reach the full extent of potential wave energy, ultimately helping the shift from fossil fuels. An early comparative study by Reikard (2009) supported a time-varying parameter approach, attributing the weakness of the neural network model to inadequate architecture and optimisation for that dataset. Hybrid models have been found to have the potential to achieve accurate predictions. Real-life application of wave energy control is difficult as it depends on accurate predictions of future waves. Li et al. (2018) explored the use of deep learning, namely ANNs, and showed that the model was able to provide accurate predictions, which substantially increased the average energy absorption from 60% to 80%. However, the control efficiency could still be further developed and improved as it was slightly lower than the optimal level. Avila et al. (2020) showed that using ANNs and fuzzy interference systems (FIS) proved to be effective tools to accurately predict wave power at any point in deep oceanic waters, even with a small dataset of a few months collected from buoys in the Micronesian region.

Recently, Giles et al. (2021) explored the issue caused by sun glint for high-resolution red-green-blue (RGB) imagery collected by drones over shallow marine environments. An artificial neural network model was developed to automatically detect and classify the sun glint in high-resolution aerial imagery. The model was supplied with a highly imbalanced dataset, with the pixels of sun glint accounting for only 1.19% of the training dataset. Despite this, 99.18% of overall predictions were correct. It was also shown that large hydropower plants could have high environmental impacts. Bortoluzzi et al. (2022) used Data Envelopment Analysis (DEA) and an artificial neural network to accurately predict the local impact of such projects. While the DEA allowed the environmental impacts to be ranked, the ANN allowed the assessment of the size of the local environmental impact. In other words, they created a hybrid DEA-ANN decision-making approach, which enables a more informed evaluation of hydroelectric generation projects. The GRU-LSTM hybrid model of Ma et al. (2023) successfully predicted water levels in cascade hydropower stations at different time scales. Such information is vital for irrigation and flood control. Authors note prediction errors associated with downstream tributary backwater jacking could be significantly reduced by adding downstream tributary flow as an additional parameter in the dataset. The LSTM parameters implemented the Archimedes optimisation algorithm. The output results of the GRU and LSTM were weighted. This resulted in increased accuracy of the water levels predicted. The authors highlight the use of a semisoft threshold function to improve the model in various ways, such as eliminating the noise of the original hydrological dataset.

6.2. Reservoir operation

Reservoirs provide a plethora of services, including the provision of freshwater supply. On the other hand, groundwater level fluctuation is subject to factors such as changes in precipitation during different seasons. National Thailand (2019) pointed out that the Vajiralongkorn Dam in Kanchanaburi was at 51% capacity with 4500 million cubic metres of water, down from 70% the same time the previous year, highlighting the harsh reality of dams drying up due to climate change. Given this fact, decision-makers are under more pressure to be aware of potential shortages in the future. Therefore, accuracy in predicting the water balance of a reservoir is crucial.

Artificial neural networks (ANN) have been applied by Hadiyan et al. (2020) to accurately forecast the Sefidroud Dam reservoir inflow. Their study compared different types of static and dynamic ANNs, which included static feedforward neural networks (FFNN), nonlinear autoregressive (NAR) neural networks, and nonlinear autoregressive neural networks with exogenous inputs (NARX). The models were trained using two input variables, namely, the monthly inflow discharge and the precipitation data. The architectures were optimised by adjusting the number of neurons within the hidden layers. They found that the dynamic NAR model outperformed the other two models and could predict high inflows while achieving the lowest RMSE values. They evidenced that the most optimum number of time delays was 12 for the input variable as the model could perform computation more accurately. They also attempted to use dynamic artificial neural networks instead of static ones for forecasting discharge inflows. Recurrent neural networks have also been used to forecast water levels to improve water resource management, and long short-term memory (LSTM) models have proved to be efficient for this purpose, achieving an accuracy of 97.05% (Ren et al., 2020).

Amongst the main hydrological processes impacting the sustainable planning and management of river, dam operation and reservoir capacity is suspended sediment load (SSL). AlDahoul et al. (2022) successfully demonstrated the application of ML models to accurately classify suspended sediment load SSL using the data from the Johor River in Malaysia. The analysed models include extreme gradient boosting XGB, random forest, support vector machine, multi-layer perceptron, and k-nearest neighbours. The XGB model exhibited superior classification performance over the other ML techniques. The model used several parameters, such as environmental factors influencing the SSL pattern, while using two different time scales. Nonetheless, they demonstrated that most of the ML models achieved acceptable classification results.

7. Water distribution and drainage systems

7.1. Water distribution systems

As water demands increase and freshwater availability decreases, water resource mapping (WRM) becomes a key aspect of water resource management. Water resource managers need to know where the next set of potential resources are to use them in their plans for the future. Therefore, accurate predictions are imperative to ensure the availability of freshwater supply is over- or underestimated during the planning. Due to inadequate information, traditional approaches for WRM, such as water spectral indices (WSI), reach an impasse with high-resolution multispectral images. This can be problematic for more complex areas. To provide an alternative approach to mediate the issue, K. Chen et al. (2020) deployed a water body extraction neural network (WBE-NN) model for a more accurate surface water resource mapping. This approach outperformed previous methods (e.g., Feng et al., 2018; Nandi et al., 2017) with reduced processing time and a reduction of underestimated water areas.

Water distribution networks (WND) are crucial infrastructure systems that provide potable water to the public. However, according to Interreg Central Europe (2020), up to 50% of water is lost in some parts of Europe, with an average of 26% due to various structural problems, including poor water pressure management, deteriorated infrastructure, and leakages. For instance, the Consumer Council for Water (2017) stated that England and Wales collectively have a water leakage loss of 3.1 billion litres daily. Many traditional approaches have been undertaken to resolve water leakage issues; however, these methodologies are limited as they need to consider the complex and nonlinear deterioration of the infrastructures over time. To resolve the issue of leakage detection, Arsene et al. (2012) explored the use of deep learning combined with graph theory.

Water distribution systems require adequate pressure management to sustain many operational aspects, which include demand control, maintenance, water leakage and failure management, cost reductions, and energy efficiency. Non-revenue water is largely attributed to water that is lost through leakage within the distribution network, thus resulting in substantial amounts of water loss through leakage. This increases operational costs, impacting the economic value of water companies. Traditional approaches for pressure monitoring often leave high uncertainties about pressure values at the nodal points that do not have sensors on them. Ridolfi et al. (2014) used artificial neural networks with a combination of the entropy-based methodology, which was outlined as shifting towards conditions of the highest order. The study found that optimal sensor placement on nodes could be achieved by finding the best trade-off between sampling design and model accuracy.

Other studies show the successful use of neural networks for leakage or contamination detection within a water distribution system. Rutkowski and Prokopiuk (2018) used learning vector quantisation (LVQ) neural networks to pinpoint contamination locations within a water distribution system in Poland, whereas Zhou et al. (2019) used a convolutional neural network as part of a novel burst location identification framework. Hu et al. (2021) proposed a novel approach to leakage detection within a water distribution system using multiscale fully convolutional networks integrated with spatial clustering of applications with noise. This approach outperformed k-nearest neighbour (KNN), support vector machine (SVM) and naive bayes classifier (NBC) by 28%, 78%, and 72%, respectively.

Water resource carrying capacity (WRCC) is an essential aspect of urban planning, which aims to balance out the amount of water demand concerning the available water resources within an urbanised area. Analysis of the WRCC of a city helps prevent the exploitation and degradation of the water resources and environment while ensuring a sustainable standard of living for the people. However, addressing this issue depends on multiple input variables, which become far too complex and reduce the accuracy of the predictions. Yu et al. (2020) proposed two simple types of feedforward neural networks (FNN) based on the normalisation value (NV) and error correction to address these issues.

Almheiri et al. (2021) outlined the superior performance of deep learning compared to other machine learning methodologies, e.g., survival random forest (SRF). However, since the amount of data available controls DL approach, it is therefore limited as pipe failure data are not widely scarce. They developed a hybrid model using an ANN-based method and integrated an ML process to predict the hazard ratio of water pipes. The performance of ML approaches (e.g., SRF) decreased as the training shots decreased, whereas the stability of the hybrid model remained constant despite the decrease in the training shots. The authors suggested the two learning phases allow the hybrid to effectively generalise, while one phase was used in the baseline approaches. Garðarsson et al. (2022) successfully demonstrated strong performance of Graph Neural Networks (GNNs) to predict pressure values in water distribution networks in order to detect leakage and localisation. Results were evaluated by the benchmark set in the Battle of the Leakage Detection and Isolation Methods challenge (BattLeDIM by Vrachimis et al. (2020)). The authors noted that the model was limited by false positives; however, the GNN model could obtain the highest economic score among the contestants, suggesting the model was still considered a viable approach to leakage detection. More recently, Yu et al. (2023) implemented ML methods with piezoelectric accelerometers installed within real-life pipe networks across several cities in China that classified vibration signals in order to detect leakages within the systems. They demonstrated that a pre-trained compact CNN with 18 deep learnable layers with the ability to classify images into 1000 classes, namely SqueezeNet, performed the best and showed a 95.15% in leak-detection accuracy compared to the other ML approaches, which included SVM, DTR and KNN. They also demonstrated that larger dataset enabled SqueezeNet to achieve more accurate results.

7.2. Water drainage system

The advent of advanced sewage and drainage systems can be traced back to the Indus Valley Civilisation around 3000 BC. This historical infrastructure spanned 91 cm across and 1.5 m in depth as a watertight sanitary drainage system (Harappa, 2020). Nowadays, natural processes required for drainage systems, namely the infiltration, which enables water to move into the ground easily, is hindered and reduced in urbanised areas. Therefore, increased stormwater can easily overwhelm surface water drainage systems of urbanised areas. Pollutants and contaminants within the system can potentially be released and have serious consequences on public health, as well as the health of any surrounding organisms. Concerns over climate change and future projections of heavier rainfall can present a challenge to decision-makers and drainage engineers. If drainage systems cannot function properly, urban flooding is inevitable and may eventually lead to various issues for both the public and the environment.

An important aspect when designing drainage systems is understanding the rainfall-runoff relationship for any given catchment. Gong et al. (1996) and Loke et al. (1997) have attempted to address this issue using ANNs models as a predictive tool for urban stormwater drainage. Loke et al. (1997) were able to show that neural networks had a high fault tolerance, good generalisation, and a high ability to learn. However, limitations of the models included the need for substantial amounts of data for more accurate predictions, little transparency, and relatively long training times. Pektaşa and Cigizoglu (2013) highlighted the inadequate performances of ANNs, univariate autoregressive integrated moving average (ARIMA), and multivariate autoregressive integrated moving average (ARIMAX) models for time series predictions for direct runoff coefficients within large drainage basins. They proposed a hybrid ANN-ARIMA model and found that it could be generalized to enhance the computational power of the neural networks and offer for more accurate time-series predictions.

On the other hand, ANNs have also been explored to alleviate issues pertaining to stormwater and optimisation of the drainage system (Hsu et al., 2013; Rjelly et al., 2018; Mullapudi et al., 2020). An early study by Tran et al. (2007) outlined the use of neural network modelling with CCTV data to identify the deterioration of stormwater pipes made from concrete. The architecture used backpropagation weight estimation and was compared to a Monte Carlo simulation using Bayesian weight estimation. Although the neural network model outperformed the Monte Carlo simulation, the model struggled to accurately process irrelevant features, namely redundant factors such as 'soil type' and 'buried depth'. More recently, Li et al. (2019) used backpropagation neural networks (BPNN) as a monitoring tool to assess the performance of stormwater green infrastructure practices. The model was successfully able to reduce peak flow rate averages of 61% per storm event and reduce the flow volume by 33% per storm event.

Truong et al. (2021) input a 21-year dataset of water levels into a gradient tree boosting (GTB) model to forecast the water levels in the culverts within irrigation and drainage systems. The GTB consistently outperformed eight other machine learning methods. Over 91% of predicted and observed values had an error rate below 10%. The comparative common machine learning techniques such as DTR, DL, Adaboost, SVM, XGBoost, RF, and LightGBM. The resultant predictions could aid in forming a strategic approach considering water resources reallocation, affordable pumping technologies, or water rotation in times of low water levels. Zhang et al. (2022) utilised deep reinforcement learning (DRL), specifically a Duelling Double Deep Qu-learning (D3QN) strategy, to evaluate the uncertainty of control within drainage systems. DRL-based real-time control showed reduced statistical dispersion by 15.48–81.93% compared to the conventional rule-based control strategy, thus demonstrating an advantage over the rule-based strategy. The reduction in statistical dispersion specifically pertained to random and system uncertainties in monitoring water level signals within an urban drainage system.

8. Water quality monitoring

Water quality is an absolute necessity for public health and safety. However, since the 1990s, water pollution has worsened in most rivers in Africa, Latin America and Asia (United Nations Environment Programme, 2016). The global population has only increased and intensified the global demand for potable water, thus putting enormous pressure on water treatment plants. Extensively urbanised cities such as London, Hong Kong and New York experience high levels of stormwater runoff. Much of the effluents carry various types of pollutants, which lower the drinking water quality, in some cases making the water dangerous for marine life. Therefore, water treatment engineers faced various challenging issues requiring advanced and innovative solutions.

For instance, estuaries face various environmental issues, including toxic chemicals, water flow changes, and habitat loss. According to the National Biodiversity Network (2019), physical changes impact a third of the water ecology in the United Kingdom, thus hindering the natural functions of the estuaries. Many estuaries undergo large-scale conversions into urbanised areas, agricultural areas, and shipping ports. Therefore, human interference imposes a great burden on the natural environment, and a substantial number of estuarine habitats are lost, forcing more competitive survival pressures on the species inhabiting those areas. Other environmental issues include toxins within the water supply, such as Cyanobacteria, also known as blue-green algae. Human interference can haphazardly provide optimum conditions for Cyanobacteria to bloom. This includes degradation of the surrounding water quality caused by the release of fertiliser-polluted runoff from farms, eutrophication of waterways and septic tank overflows. These environments allow Cyanobacteria to thrive and multiply above a safe level for humans, animals, and plants.

Various studies have been conducted using deep learning for estimations and predictions regarding water quality, including Zhou (2020), who used transfer-based LSTMs, and Yu and Qu (2020), who used radial basis function neural networks. Zhang and Hu (2020) used difference-gated neural networks, and Y. Chen et al. (2020) used deep cascade forests. Jouanneau et al. (2014) found that monitoring Biochemical Oxygen Demand (BOD), a key water quality indicator, required more time and effort to detect. Ma et al. (2020) addressed this issue by developing a deep matrix factorization (DMF) combined with deep neural networks (DNN) in a New York City (United States) harbour. The proposed model showed strong computational power, superior to other machine learning algorithms such as gradient-boosted decision trees, random forest, and support vector regression. Traditional linear methods, such as Ridge, LR, and LASSO, were also used as a benchmark but underperformed compared to the machine learning methods.

The history of modern-day water supply infrastructures can be traced back to the 1600s in Medieval London (Water History, 2020). Newhart et al. (2019) found that water treatment plants are excellent subjects for neural network studies due to the large quantity of historical data that is usually available and easily accessible. Several studies have shown that ANNs outperform other machine learning algorithms for investigating the operations of the water treatment plant (Guo et al., 2015; Ghaedi and Vafaei, 2017; Najafzadeh and Zeinolabedini, 2019). These operations ranged from predictions for membrane fouling in the filtration systems of a water treatment system to predictions for real-time coagulant dosage (Dharman et al., 2012; Kim and Parnichkun, 2017; Bagheri et al., 2019). Alternatively, Zhang et al. (2019a, 2019b) used ANN with genetic algorithms to predict the performance of drinking water treatment plants under varying pressures and stresses to effectively manage the water treatment plant.

Wastewater treatment is imperative to ensure the health and safety of the public and the surrounding environment. In 2015, the United Nations International Children's Emergency Fund (UNICEF) estimated that 1.8 billion people have no other water source except water contaminated by faecal matter. Therefore, a significant part of the world's population is highly exposed to various water-related diseases, including polio, cholera and typhoid. The United Nations Educational, Scientific and Cultural Organization (2017) reported that 80% of inadequately treated wastewater is released into the environment worldwide. The pollutants in this water can severely impact human health and the surrounding ecosystem, such as decaying organic matter, reducing oxygen availability, and essentially killing the aquatic inhabitants.

Proper management of wastewater treatment is pivotal before effluent can be safely discharged back into the environment. Ráduly et al. (2007) used ANNs to evaluate the performance of wastewater treatment plants, while Shi and Xu (2018) proposed a model based on a stacked denoising auto-encoders deep learning network to predict biofilm system's performance under various wastewater treatment plant operations. Zhang et al. (2018) used LSTMs to forecast flow to optimise inter-catchment wastewater transfer and reduce overflow, and Niu et al. (2020) used genetic algorithms integrated into deep belief networks to accurately predict effluent quality and improve process monitoring. Bhagat et al. (2020) provided a critical analysis of the development of artificial intelligence for modelling the removal of heavy metals within wastewater. The approaches investigated included ensemble models, various metaheuristics, different ANN models, and unsupervised methods. Recently, Sang-Soo et al. (2020) used a convolutional neural network (CNN) and long short-term memory (LSTM) combined with a deep learning approach to predict the water level and water quality in the Nakdong river basin. The study highlighted the proposed model's performance and ability to capture the temporal variations of the pollutants in the Nakdong River basin.

Zhu et al. (2022) successfully used enhanced feed-forward neural networks to predict biochemical oxygen demand (BOD) and ammonia nitrogen (NH3–N) water quality indicators within wastewater treatment plants. The highly accurate model obtained a mean error of less than 10% with an R2 of 90%, thus improving on the previous feed-forward neural network with the least square support vector machine (FFNN-LSSVM) model. However, the authors suggested that the data obtained from real-time monitoring should be used to inform future research and improve the model performance. Yang et al. (2023) demonstrated the sufficient accuracy of LSTM network in the task of forecasting the effluent quality of a constructed wetland. Their model could outperform other predictive ML methods including multiple linear regression, backpropagation neural network

(BPNN), and a GA-BPNN-hybrid neural network (genetic algorithm as an optimisation method integrated into a BPNN model) to resolve local minima issues. They showed that their data exhibited significant effluent population fluctuations. A moving average method was applied to smooth the data, improving the accuracy of the traditional and hybrid neural networks. Ibrahim et al. (2023) outlined using ANNs to successfully predict the water quality index (WQI). The authors used principal component analysis (PCA) to identify the sources of pollution within the Terengganu River and reflect the general conditions. They applied three ANN models with differing input layers to predict the water quality index (WQI) of the river. The best-performing ANN was found to be the one that used the raw data as the input layer, as opposed to principal component factor scores (obtained from the previously conducted PCA).

9. Flood management and water-retaining structures

9.1. Flood prediction

Flooding poses a serious risk to many people worldwide, with many regions of the earth impacted by this natural disaster. Flooding is caused by a wide range of factors, including (i) heavy, prolonged rainfall events, which are more likely to rise in the future as a consequence of climate change, (ii) urbanisation., which substantially increases the surface water runoff and impedes the rate of infiltration, or (iii) infrastructure failure such as overtopping of dams. The impacts of flooding can have a substantial economic burden, particularly in the developing world. Some studies (e.g., Ward et al., in 2017; Peduzzi in 2017; Alfieri et al., 2018) anticipate the global economic impact of flooding to cost approximately $1 trillion by 2050. Other impacts include mass migration, socio-psychological implications, loss of livelihood and property and, in more severe cases, loss of life. According to a report presented by the United Nations (2015), 2.3 billion people were affected by flooding, with a significantly high death toll of 157,000 people between 1995 and 2015. Future flooding events have been predicted to become more frequent and more intense than they have been in the past. Therefore, to sufficiently mitigate and manage the consequences of flooding, exploring innovative solutions and technologies that enhance the accuracy of predicting flood occurrences is imperative.

Conventional methodologies include prediction using flood inundation models (Salvadore et al., 2015; Gires et al., 2015; Teng et al., 2017). However, these models can only simulate results based on distinct types of flooding, and complete real dynamic processes are omitted, resulting in the decayed accuracy of the projections. Fenech et al. (2019) attempt to follow a similar methodology but include dynamic processes. They aimed to improve this model by using a model that divides the irregular urban area into various grid cells. The proposed model considered the characteristics of the urban environment, including urban drainage systems and impermeable surfaces. To evaluate the model, the authors attempted to reproduce the flood in Lafayette Parish in Louisiana in 2016. Results showed that due to coarse resolutions, simulations could not reproduce the flood regions of the 2016 Lafayette Parish flooding. However, spatial patterns were observed after the model resolution was refined. Fang et al. (2019) introduced deep learning for flood prediction and proposed an integrated LSTM and reduced-order-model (ROM) framework to perform time series prediction and prescriptive analysis on flooding. Their study found that the LSTM-ROM model outperformed the full model and maintained its accuracy in predicting flooding. However, they found that when lead time is extended, the predictive accuracy decreases.

Bui et al. (2020) introduced a novel approach using deep learning neural networks to aid in forecasting the likelihood of flash floods. This type of ANNs architecture was selected due to its ability to represent and process highly complex input data and to produce highly accurate projections despite the non-linearity of the given data (Lewis, 2016). Their study was specifically designed to address the challenges in regions susceptible to a high frequency of tropical storms. Therefore, the model was based on real-life data collected in the northwest mountainous region of Vietnam. The geographic information system (GIS) input dataset included the slope, lithology, rainfall, soil type, elevation, steam density, curvature, and normalised difference vegetation index (NDVI). All nine factors influenced the susceptibility of flash flooding within the area. The influencing factors were selected based on the information gain ratio method proposed by Quinlan (1986) and Dai and Xu (2013), thus eliminating the need for data collection on unnecessary factors.

Hosseiny's (2021) study utilised U-net, an advanced CNN, to predict river flood depth and extent. The results surmised an improved accuracy in predicting the maximum flood depth by 29%. Löwe et al.'s (2021) research also successfully implemented advanced convolutional neural networks, U-Net, to predict urban pluvial flood water depth. It was found that deeper networks improved the prediction until reaching a limit of around 28 million trainable parameters. It was noted that too many datasets led to overfitting and increased prediction errors. The dataset that led to the model performing the best included a combination of terrain aspect, curvature, depth of depressions, flow accumulation and imperviousness. Ahmed et al. (2021) found exponential Gaussian process regression (GPR) accurately predicted the daily water levels in a river subject to annual flash flooding in Malaysia based on data collected from 1990 to 2019. The GPR model outperformed several other machine learning models such as linear regression (LR), interaction regression (IR), robust regression (RR), stepwise regression (SR), support vector regression, boosted trees ensemble regression (BOOSTER), bagged trees ensemble regression (BAGER), XGBoost, and tree regression (TR). The GPR was further used to predict water levels based on 10-day minimum and maximum water levels and could forecast the extremes of the water levels. The authors of the study denote the study was limited by data availability.

Ramayanti et al. (2022) explored the generation of flood susceptibility mapping, where they implemented two deep learning architectures to the problem: group method of data handling (GMDH) and CNN. The study was centred around the March 2019 flood in the Beria Area, Mozambique. The models were both able to produce similar mapping, where lower-sloped areas (i.e., areas along the river) were at a higher risk of flooding. The CNN performance indicator, RMSE value, was four times lower than the RMSE value derived from GMDH. This showed that CNN could generate an accurate flood susceptibility map more than the GMDH. Sorkhabi et al. (2023) employed CNN and LSTM to predict the variability in sea level and flooding to measure coastal city resilience. Variables included wind speed, sea surface temperature, precipitation, and mean sea level. The study found that deep learning approaches offered good predictive accuracy in the resilience of the city against flooding due to the variable sea level. However, future works suggested are to incorporate more parameters, such as updated satellite data, to improve the accuracy of the models.

9.2. Water retaining structures

Throughout human history, dating back more than 5000 years, according to Biswas and Tortajada (2010), water-retaining structures have been constructed in many places worldwide. Dams provide many benefits, although their fundamental purpose is to facilitate water storage. These benefits include, but are not limited to, flood control, hydropower and human consumption. Currently, there are 50,000 of these large hydraulic structures (Tata and Howard, 2016) being used worldwide, of which a large majority are embankment dams. The British Dam Society (2019) attributes the most common dam failure modes to overtopping during floods.

The health and structural integrity of dams are crucial since the consequences of failure can be severe. Therefore, understanding dam behaviour and failure mechanisms is vital. De Granrut et al. (2019) explored using ANNs to analyse the behaviour of piezometric data on arch dams, focusing on the rock-concrete interface to monitor uplift pressures on the dam. The study highlighted the limitations of traditional multi-linear regression (MLR) models, such as the Hydrostatic-Season-Time (HST) model, which are commonly used across engineering practices to monitor dams (Crépon and Lino in 1999; Penot et al., in 2005; Léger and Leclerc in 2007). The advantage of using HST is that only the reservoir level is required and performs well only under certain circumstances. On the other hand, various mathematical approaches have been proposed to model dam seepage (Ding and Han, 2017). Cui and Zhu (2009) successfully implemented a three-dimensional finite element method integrated with genetic algorithms; however, issues with convergence and basic operators in the genetic algorithms impacted the model's accuracy. Zhang et al. (2020) successfully applied ANNs integrated with a three-dimensional finite element model to forecast the regions of weakness (particularly seepage) of concrete dam foundations. Unlike the HST model, ANNs enable the capture of the non-linearity of the piezometric data, such as the leakage flows, movements, and head of the reservoir.

Overtopping occurs when the dam's design, such as the freeboard, is not sufficient to cater to the actual requirements, which may change over time. Hence, a suitable design during the initial construction may no longer be appropriate later due to the changes in conditions. The likelihood of overtopping is further exacerbated during extreme weather conditions. For example, due to fluctuations caused by the weather, the head of the water rises above the designed freeboard, which leads to overtopping. The Environment Agency (2018) reports that the projections show increased winter precipitation over the United Kingdom because of climate change. Although seasonal variation is expected, there will be times during the year when dams will be subjected to store more water due to the high precipitation, increasing the risk of overtopping. As the years go on, the trend of a rainfall event is expected to further increase the risk of overtopping. Huang et al. (2003) used convolutional ANNs for coastal water level predictions. However, this method requires large amounts of long-term historical data, which is not always readily available. Fuzzy logic parameters integrated into ANNs provide effective estimations of water levels under uncertainty; however, they do not give insight into the parameters' uncertainties alone (Alvisi and Franchini, 2011). Yang et al. (2019) applied recurrent ANNs to simulate reservoir operations using inflow, storage and climate data. In this study, the authors used a long-short term memory (LSTM), nonlinear autoregressive models with exogenous input (NARX) and a NARX-based genetic algorithm, and they found that the latter was able to outperform the other models.

Ren et al. (2021) implemented an interpretable mixed attention mechanism long short-term memory (MAM-LSTM) model to predict displacement associated with concrete dams. The authors found success in their two-staged encoder approach. The highly influential factors were adaptively selected by the factor attention mechanism module. The temporal attention mechanism module, in contrast, was able to select the relevant hidden states. This model outperformed classical statistical modelling and other deep learning and machine learning models. Fan et al. (2022) utilised a transfer learning approach, MA-AttUNet. This sophisticated methodology applied previous knowledge from a source domain to underwater crack image segmentation. The knowledge transfer occurs using a multi-level adversarial transfer network. An attention mechanism also limited background noise during detection. Although the model exhibited poor real-time performance, it was able to accurately identify underwater dam crack images. Nonetheless, the model outperformed other methods at the time of the study. Zhang et al. (2023) used a unifying transformer encoder integrated into a CNN architecture for pixel-level dam crack detection. The proposed model demonstrated flexibility and was able to adapt to a variety of scenarios. Although the model performed well against quantitative indicators, the authors showed that the model's accuracy in detection was critically impacted by weak or disturbing background information. They also highlighted that the model's speed was slightly lower than comparative machine learning models, thereby suggesting that future works could include a lightweight deep learning architecture for faster training.

10. Conclusions, open issues, and prospects

Machine learning techniques have successfully been used to identify patterns within nonlinear datasets. This study explored the various ML techniques that have been applied within the realm of water resources management. Various Machine Learning techniques have found significant applications for prediction purposes, ranging from pure forecasting to estimating certain parameters of optimisation models. Particularly, implementing artificial neural networks has found great success in recent years.

Proactive and effective water management requires accurate prediction, and several studies have shown that standalone deep learning models could outperform conventional machine learning models, albeit the data characteristics could substantially affect their performance. Specifically, LSTM networks have been proven to exhibit reliable forecasting performance and even outperform ANN models, traditional machine learning models, and established physics-based hydrological models. Complexifying the architecture of LSTM-based models (via stacked structure) has not substantially improved forecasting performance. More complex ML models require more data, and thus, the complexity of the deep learning model should be in accordance with the data. However, the performance of standalone deep learning models could sometimes be limited and unable to effectively capture features from multivariate time series.

Presently, more studies have considered hybrid ML techniques, such as hybrid ANNs, as they have shown superior computational power over traditional ANNs architectures. Hybrid models combining classic deep learning models such as the LSTM or GRU and decomposition algorithms (WT, EMD, and VMD) have shown good performance and should, therefore be further developed. The development of hybrid machine learning models has often yielded comparable performance in terms of forecasting accuracy. Hence, these models could still be further improved and developed, especially for long forecasting horizons, as the predictive accuracy has always decreased with increasing lead time. Hybrid deep learning models should be more developed than standalone deep learning models, considering their superiority in terms of prediction performance.

Physics-hybrid models, which combine data-driven models and physical models, have also proven to improve prediction performance. Physical-based hybrid models are commonly either developed by feeding the ML model with the simulation outputs of physical-based models, or by forecasting its errors. When forecasting the error, the deep learning models can detect the location of most errors made by the physical-based models. When using the output of physical-based models as input for the ML model, its contribution should be first assessed to ascertain it would add positive impact on model performance.

Other advanced deep learning architectures, such as transformers (Polosukhin et al., 2017), have yet to be tested in water resources management. Transformers have so far been successfully used to design neural networks in various application domains, including natural language processing, genomic sequences, time series data, and signal processing. Such models are known for their general structure, which includes an additional layer between the encoder and decoder, enabling them a high degree of parallelisation and, hence, faster training. This could be a valuable feature when handling complex data, which is very valuable given that several studies have shown that several hydrological/meteorological variables could contribute positively to prediction performance. Recent studies (e.g., Janner et al., 2021) highlighted how transformer architectures can be used to simplify reinforcement learning by formulating it into a single big sequence. Such an approach provided more capacity and power to reinforcement models in their attempt to address decision-making problems via the distributions of rewards and actions over sequences of states. Furthermore, transformer architecture offers some promising features for dynamics prediction as well as long-horizon dynamics prediction, which could tremendously improve groundwater level or river streamflow forecasting.

In a data-scarce context, implementing Transfer Learning techniques could be a potential solution when developing hybridising physical-based and deep learning models. In the future, it is thus highly recommended to further employ Transfer Learning to improve ML model performance, particularly for long forecasting horizons, as predictive accuracy has always been shown to decrease with increasing lead times. The implementation of Transfer Learning could substantially improve the performance of hybrid deep learning models, and thus enable more informed decision-making process in the realm of water resource management and flood defence applications.

In the real-world context, ML has proven to be a powerful tool in water resources management, providing insights, predictions, and optimisation capabilities. The practical application of ML in the water sector has taken a wide disparity of forms, depending on the intended use or desired benefits. For instance, ML has successfully been used to develop a Smart Water Networks in Barcelona, Spain, where ML and IoT (Internet of Things) technologies were implemented to improve water efficiency and reduce losses in the distribution network (Shahra et al., 2019). This was done by monitoring water quality, detecting leaks, and optimising water distribution using sensors and data analytics. Another example was the application of ML for burst locations in water distribution network in Jiangsu province, east China (Zhou et al., 2019). They correctly located 57 of 58 synthetic bursts in the system.

Another practical application of ML is the development and deployment of decision support systems (DSS) to help water resources managers and authorities to make informed decisions. DSS have also been greatly beneficial for water resources allocations in several countries, including the US (WRF-Hydro), Australia (AQUATOR), or the Netherlands (HydroNET). These often leverage machine learning to analyse complex data including – but not limited to - satellite imagery, real-time sensor data, and hydrological and weather data, to make predictions and assist decision-makers. ML algorithms have also been implemented to develop an early warning system that helps residents and authorities take preventive measures during heavy rainfall events (Dong et al., 2022). Weather patterns, river levels, and historical flood data are first analysed to enable the system to provide early warnings. All in all, Machine learning has become a valuable asset in the water sector, providing valuable insights, predictions, and optimisation capabilities applicable in real-world practice to enhance sustainable water use and management, and subsequently improving socio-economic development, healthy ecosystems and human existence itself.

Uncited references

, Zhang et al., 2023

CRediT authorship contribution statement

Ashraf A. Ahmed: Writing – review & editing, Supervision, Conceptualization. **Sakina Sayed:** Writing – review & editing. **Antoifi Abdoulhalik:** Writing – review & editing, Conceptualization. **Salissou Moutari:** Writing – review & editing. **Lukumon Oyedele:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgement

The authors would like to thank three anonymous reviewers and the editors for their valuable comments that have significantly improved this paper. This work was partially funded by EPSRC project reference 2339403 to S Sayed and A Ahmed.

References

Agrawal, R., Srikant, R., 1994. Fast algorithms for mining association rules, Proceedings of the 20th International Conference on Very Large Data Bases. VLDB, Santiago, Chile, pp. 487–499.

Agresti, A., 2011. An Introduction to Categorical Data Analysis, second ed. Wiley.

Agresti, A., Franklin, C.A., 2011. Statistics: the Art and Science of Learning from Data, third ed. Pearson.

Ahmadi, A., Olyaei, M., Heydari, Z., Emami, M., Zeynolabedin, A., Ghomlaghi, A., Daccache, A., Fogg, G.E., Sadegh, M., 2022. Groundwater level modeling with machine learning: a systematic review and meta-analysis. Water 14 (6), 949. https://doi.org/10.3390/w14060949.

Ahmed, A.N., Yafouz, A., Birima, A.H., Kisi, O., Huang, Y.F., Sherif, M., Sefelnasr, A., El-Shafie, A., 2021. Water level prediction using various machine learning algorithms: a case study of Durian Tunggal river, Malaysia. Eng. Appl. Comput. Fluid Mech. 16 (1), 422–440. https://doi.org/10.1080/19942060.2021.2019128.

Akbarian, M., Saghafian, B., Golian, S., 2023. Monthly streamflow forecasting by machine learning methods using dynamic weather prediction model outputs over Iran. J. Hydrol. 620 (Part B), 129480. https://doi.org/10.1016/j.jhydrol.2023.129480. . ISSN 0022-1694.

Al-Ghobari, H.M., El-Marazky, M.S., Dewidar, A.Z., Mattar, M.A., 2018. Prediction of Wind Drift and Evaporation Losses from Sprinkler Irrigation Using Neural Network and Multiple Regression Techniques, vol. 195. Agricultural Water Management, pp. 211–221. https://doi.org/10.1016/j.agwat.2017.10.005.

AlDahoul, N., Ahmed, A.N., Allawi, M.F., Sherif, M., Sefelnasr, A., Chau, K.W., El-Shafie, A., 2022. A comparison of machine learning models for suspended sediment load classification. Eng. Appl. Comput. Fluid Mech. 16 (1), 1211–1232. https://doi.org/10.1080/19942060.2022.2073565.

Alfieri, L., Cohen, S., Galantowicz, J., Schumann, G.J.P., Trigg, M.A., Zsoter, E., Prudhomme, C., Kruczkiewicz, A., de Perez, E.C., Flamig, Z., Rudari, R., Wu, H., Adler, R.F., Brakenridge, R.G., Kettner, A., Weerts, A., Matgen, P., Islam, S.A.K.M., Salamon, P., 2018. A Global Network for Operational Flood Risk Reduction, vol. 84. Environmental Science & Policy, pp. 149–158. https://doi.org/10.1016/j.envsci.2018.03.014.

Alhumoud, J.M., 2008. Freshwater consumption in Kuwait: analysis and forecasting. J. Water Supply Res. Technol. - Aqua 57 (4), 279–288. https://doi.org/10.2166/aqua.2008.036.

Alibabaei, K., Gaspar, P.D., Assunção, E., Alirezazadeh, S., Lima, T.M., 2022. Irrigation optimization with a deep reinforcement learning model: case study on a site in Portugal. Agric. Water Manag. 263, 107480. https://doi.org/10.1016/j.agwat.2022.107480. . ISSN 0378-3774.

Allawi, M.F., Abdulhameed, U.H., Adham, A., Sayl, K.N., Sulaiman, S.O., Ramal, M.M., Sherif, M., El-Shafie, A., 2023. Monthly rainfall forecasting modelling based on advanced machine learning methods: tropical region as case study. Eng. Appl. Comput. Fluid Mech. 17 (1), 2243090. https://doi.org/10.1080/19942060.2023.2243090.

Almheiri, Z., Meguid, M., Zayed, T., 2021. Failure modelling of water distribution pipelines using meta-learning algorithms. Water Res. 205, 117680. https://doi.org/10.1016/j.watres.2021.117680. . ISSN 0043-1354.

Alsumaiei, A.A., 2020. A nonlinear autoregressive modeling approach for forecasting groundwater level fluctuation in urban aquifers. Water 2020 12 (3), 820. https://doi.org/10.3390/w12030820.

Alvisi, S., Franchini, M., 2011. Fuzzy neural networks for water level and discharge forecasting with uncertainty. Environ. Model. Software 26 (4), 523–537. https://doi.org/10.1016/j.envsoft.2010.10.016.

Amari, S.-I., 1972. Learning patterns and pattern sequences by self-organizing nets of threshold elements. IEEE Transact. C 21, 1197–1206.

Antunes, A., Andrade-Campos, A., Sardinha-Lourenço, A., Oliveira, M.S., 2018. Short-term water demand forecasting using machine learning techniques. J. Hydroinf. 20 (6), 1343–1366. https://doi.org/10.2166/hydro.2018.163.

Arsene, C.T.C., Gabrys, B., Al-Dabass, D., 2012. Decision support system for water distribution systems based on neural networks and graphs theory for leakage detection. Expert Syst. Appl. 39 (18), 13214–13224. https://doi.org/10.1016/

j.eswa.2012.05.080.

Avila, D., Marichal, G.N., Padrón, I., Quiza, R., Hernández, Á., 2020. Forecasting of Wave Energy in Canary Islands Based on Artificial Intelligence, vol. 101. Applied Ocean Research, 102189. https://doi.org/10.1016/j.apor.2020.102189.

Azizpour, A., Izadbakhsh, M.A., Shabanlou, S., Yosefvand, F., Rajabi, A., 2021. Estimation of water level fluctuations in groundwater through a hybrid learning machine. Groundwater Sustain. Develop. 15, 100687. https://doi.org/10.1016/j.gsd.2021.100687. . ISSN 2352-801X.

Bagheri, M., Akbari, A., Mirbagheri, S.A., 2019. Advanced Control of Membrane Fouling in Filtration Systems Using Artificial Intelligence and Machine Learning Techniques: A Critical Review, vol. 123. Process Safety and Environmental Protection, pp. 229–252. https://doi.org/10.1016/j.psep.2019.01.013.

Bai, T., Tahmasebi, P., 2023. Graph neural network for groundwater level forecasting. J. Hydrol. 616, 128792. https://doi.org/10.1016/j.jhydrol.2022.128792. . ISSN 0022-1694.

Baille, M., Baille, A., Laury, J.C., 1994. A simplified model for predicting evapotranspiration rate of nine ornamental species vs. climate factors and leaf area. Scientia Horiculturae 59 (3–4), 217–232. https://doi.org/10.1016/0304-4238(94)90015-9.

Banadkooki, F.B., Xiao, Y., Malekinezhad, H., Hosseini, M.M., 2022. Optimal allocation of regional water resources in an arid basin: insights from Integrated Water Resources Management. AQUA – Water Infrastruct., Ecosyst. Soc. 70 (8), 910–925. https://doi.org/10.2166/aqua.2022.029.

Bennett, C., Stewart, R.A., Beal, C.D., 2013. Ann-based residential water end-use demand forecasting model. Expert Syst. Appl. 40 (4), 1014–1023. https://doi.org/10.1016/j.eswa.2012.08.012.

Bhagat, S.K., Tung, T.M., Yaseen, Z.M., 2020. Development of artificial intelligence for modeling wastewater heavy metal removal: state of the art, application assessment and possible future research. J. Clean. Prod. 250, 119473. https://doi.org/10.1016/j.jclepro.2019.119473.

Bilali, A.E., Taleb, A., 2020. Prediction of irrigation water quality parameters using machine learning models in a semi-arid environment. J. Saudi Soc. Agricult. Sci. https://doi.org/10.1016/j.jssas.2020.08.001.

Bishop, C.M., 2011. Pattern Recognition and Machine Learning (Information Science and Statistics). Springer, New York.

Biswas, A.K., Tortajada, C., 2010. Development and large dams: a global perspective. Int. J. Water Resour. Dev. 17 (1), 9–21. https://doi.org/10.1080/07900620120025024.

Bortoluzzi, M., Furlan, M., Dos Reis Neto, J.F., 2022. Assessing the impact of hydropower projects in Brazil through data envelopment analysis and machine learning. Renew. Energy 200, 1316–1326. https://doi.org/10.1016/j.renene.2022.10.066. . ISSN 0960-1481.

Bovas, A., Johannes, L., 1983. Statistical Methods for Forecasting. Wiley & Sons, Inc.

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32.

Breiman, L., Friedman, J.H., Olshen, R.A., Stone, C.J., 1984. Classification and Regression Trees. Wadsworth, Inc, Belmont California.

British Dam Society, 2019. Historic dam failures and recent incidents. Available at: https://www.engineersireland.ie/EngineersIreland/media/SiteMedia/groups/Divisions/civil/Historic-Dam-Failures-slides.pdf?ext=.pdf. (Accessed 15 February 2020).

Brophy, L.S., Greene, C.M., Hare, V.C., Holycross, B., Lanier, A., Heady, W.N., O'Connor, K., Imaki, H., Haddad, T., Dana, R., 2019. Insights into estuary habitat loss in the western United States using a new method for mapping maximum extent of tidal wetlands. PLoS One 14 (8). https://doi.org/10.1371/journal.pone.0218558.

Bui, D.T., Hoang, N., Martínez-Álvarez, F., Ngo, P.T., Hoa, P.V., Pham, T.D., Samui, P., Costache, R., 2020. A Novel Deep Learning Neural Network Approach for Predicting Flash Flood Susceptibility: A Case Study at a High Frequency Tropical Storm Area, vol. 701. Science of The Total Environment, 134413. https://doi.org/10.1016/j.scitotenv.2019.134413.

Cai, H., Shi, H., Liu, S., Babovic, V., 2021. Impacts of regional characteristics on improving the accuracy of groundwater level prediction using machine learning: the case of central eastern continental United States. J. Hydrol.: Reg. Stud. 37, 100930. https://doi.org/10.1016/j.ejrh.2021.100930. . ISSN 2214-5818.

Chapelle, O., Scholkopf, B., Zien, A., 2006. Semi-supervised Learning. The MIT Press.

Chen, T., Guestrin, C., 2016. XGBoost: a scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. pp. 785–794. New York, NY, USA.

Chen, H., Chen, A., Xu, L., Xie, H., Qiao, H., Lin, Q., Cai, K., 2020. A deep learning CNN architecture applied in smart near-infrared analysis of water pollution for agricultural irrigation resources. Agric. Water Manag. 240, 106303. https://doi.org/10.1016/j.agwat.2020.106303.

Chen, K., Chen, H., Zhou, C., Huang, Y., Qi, X., Shen, R., Liu, F., Zuo, M., Zou, X., Wang, J., Zhang, Y., Chen, D., Chen, X., Deng, Y., Ren, H., 2020. Comparative Analysis of Surface Water Quality Prediction Performance and Identification of Key Water Parameters Using Different Machine Learning Models Based on Big Data, vol. 171. Water Research, 115454. https://doi.org/10.1016/j.watres.2019.115454.

Chen, Y., Tang, L., Kan, Z., Bilal, M., Li, Q., 2020. A novel water body extraction neural network (WBE-NN) for optical high-resolution multispectral imagery. J. Hydrol. 588. https://doi.org/10.1016/j.jhydrol.2020.125092.

Chen, M., Cui, Y., Wang, X., Xie, H., Liu, F., Luo, T., Zheng, S., Luo, Y., 2021. A reinforcement learning approach to irrigation decision-making for rice using weather forecasts. Agric. Water Manag. 250, 106838. https://doi.org/10.1016/j.agwat.2021.106838. . ISSN 0378-3774.

Cheng, M., Fang, F., Kinouchi, T., Navon, I.M., Pain, C.C., 2020. Long lead-time daily and monthly streamflow forecasting using machine learning methods. J. Hydrol. 590 (125376). https://doi.org/10.1016/j.jhydrol.2020.125376. . ISSN 0022-1694.

Cho, K., van Merrienboer, B., Bahdanau, D., Bougares, F., Schwenk, H., Bengio, Y., 2014. Learning phrase representations using RNN encoder-decoder for statistical machine translation. In: Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing. EMNLP, pp. 1724–1734.

Chu, H., Wu, J., Wu, W., Wei, J., 2023. A dynamic classification-based long short-term memory network model for daily streamflow forecasting in different climate regions. Ecol. Indicat. 148, 110092. https://doi.org/10.1016/j.ecolind.2023.110092. . ISSN 1470-160X.

Consumer Council for Water, 2017. Water leakage from UK pipes rises to over three billion litres a day. Available at: https://eandt.theiet.org/content/articles/2017/12/water-leakage-from-uk-pipes-rises-to-over-three-billion-litres-a-day/. 02/06/20.

Cortes, C., Vapnik, V., 1995. Support-vector networks. Mach. Learn. 20, 273–297.

Cover, T.M., Hart, P.E., 1967. Nearest neighbor pattern classification. IEEE Trans. Inf. Theor. 13, 21–27.

Crépon, O., Lino, M., 1999. An Analytical Approach to Monitoring. International Water Power, pp. 52–54.

Cui, H.D., Zhu, Y.M., 2009. Back analysis of seepage field of Ertan high arch dam foundation. Rock Soil Mech. 30 (10), 3194–3199.

Dai, J., Xu, Q., 2013. Attribute selection based on information gain ratio in fuzzy rough set theory with application to tumor classification. Appl. Soft Comput. 13 (1), 211–221. https://doi.org/10.1016/j.asoc.2012.07.029.

De Granrut, M., Simon, A., Dias, D., 2019. Artificial Neural Networks for the Interpretation of Piezometric Levels at the Rock-Concrete Interface of Arch Dams, vol. 178. Engineering Structures, pp. 616–634. https://doi.org/10.1016/j.engstruct.2018.10.033.

Dehghani, A., Moazam, H.M.Z.H., Mortazavizadeh, F., Ranjbar, V., Mirzaei, M., Mortezavi, S., Ng, J.L., Dehghani, A., 2023. Comparative evaluation of LSTM, CNN, and ConvLSTM for hourly short-term streamflow forecasting using deep learning approaches. Ecol. Inf. 75, 102119. https://doi.org/10.1016/j.ecoinf.2023.102119. . ISSN 1574-9541.

Dharman, S., Chandramouli, V., Lingireddy, S., 2012. Predicting total organic carbon removal efficiency and coagulation dosage using artificial neural networks. Environ. Eng. Sci. 29 (8). https://doi.org/10.1089/ees.2011.0170.

Di Nunno, F., Granata, F., 2020. Groundwater Level Prediction in Apulia Region (Southern Italy) Using NARX Neural Network. Environmental Research, p. 190. https://doi.org/10.1016/j.envres.2020.110062.

Ding, C.L., Han, H., 2017. Study on network load forecasting based on Elman neural network to improve ARIMA model. Microcomput. Appl. 33 (11), 65–68.

Docheshmeh Gorgij, A., Gh Askari, A.A. Taghipour, Jami, M., Mirfardi, M., 2023. Spatiotemporal forecasting of the groundwater quality for irrigation purposes, using deep learning method: long short-term memory (LSTM). Agric. Water Manag. 277, 108088. https://doi.org/10.1016/j.agwat.2022.108088. . ISSN 0378-3774.

Domingos, P., Pazzani, M., 1997. On the optimality of the simple Bayesian classifer under zero-one loss. Mach. Learn. 29, 103–137.

Dong, S., Yu, T., Farahmand, H., Mostafavi, A., 2022. Predictive multi-watershed flood monitoring using deep learning on integrated physical and social sensors data. Environ. Plan. B Urban Anal. City Sci. 49 (7), 1838–1856. https://doi.org/10.1177/23998083211069140.

Drucker, H., Burges, C.J.C., Kaufman, L., Smola, A., Vapnik, V., 1997. Support vector regression machines. In: Mozer, M.C., Jordan, M.I., Petsche, T. (Eds.), Advances in Neural Information Processing Systems 9. MIT Press, Cambridge, MA, pp. 155–161.

Elbeltagi, A., Deng, J., Wang, K., Malik, A., Maroufpoor, S., 2020. Modeling long-term dynamics of crop evapotranspiration using deep learning in a semi-arid environment. Agric. Water Manag. 241, 106334. https://doi.org/10.1016/j.agwat.2020.106334.

Environment Agency, 2018. UKCP18 factsheet: precipitation. Available at: https://www.metoffice.gov.uk/binaries/content/assets/mohippo/pdf/ukcp18/ukcp18-factsheet-precipitation.pdf. (Accessed 15 February 2020).

Fan, X., Cao, P., Shi, P., Chen, X., Zhou, X., Gong, Q., 2022. An underwater dam crack image segmentation method based on multi-level adversarial transfer learning. Neurocomputing 505, 19–29. https://doi.org/10.1016/j.neucom.2022.07.036. . ISSN 0925-2312.

Fang, F., Hu, R., Pain, C.C., Navon, I.M., 2019. Rapid spatio-temporal flood prediction and uncertainty quantification using a deep learning method. J. Hydrol. 575, 911–920.

Fenech, A., Wang, X., Kinsland, G., Poudel, D., 2019. Urban flood prediction under heavy precipitation. J. Hydrol. 577.

Feng, W., Sui, H., Huang, W., Xu, C., An, K., 2018. Water body extraction from very high-resolution remote sensing imagery using deep U-net and a superpixel-based conditional random field model. Geosci. Rem. Sens. Lett. IEEE 16 (4), 618–622.

Ferreira, L.B., da Cunha, F.F., 2020a. New approach to estimate daily reference evapotranspiration based on hourly temperature and relative humidity using machine learning and deep learning. Agric. Water Manag. 234, 106113. https://doi.org/10.1016/j.agwat.2020.106113.

Ferreira, L.B., da Cunha, F.F., 2020b. Multi-step ahead forecasting of daily reference evapotranspiration using deep learning. Agric. Water Manag. 178, 105728. https://doi.org/10.1016/j.compag.2020.105728.

Food and Agriculture Organization of the United Nations, 2017. Water for sustainable food and agriculture: a report produced for the G20 presidency of Germany. Available at: http://www.fao.org/3/a-i7959e.pdf. 03/08/20.

Frank, E., Trigg, L., Holmes, G., Witten, I.H., 2000. Naive bayes for regression. Mach. Learn. 41, 5–25.

Freund, Y., Schapire, R.E., 1995. A Decision-Theoretic Generalization of On-Line Learning and Application to Boosting. Lecture Notes in Computer Science. Springer berlin Heidelberg, pp. 23–37.

Frey, B., Makhzani, A., 2013. K-Sparse Autoencoders. arXiv:1312.5663.

Friedman, J.H., 1989. Regularized discriminant analysis. J. Am. Stat. Assoc. 84, 165–175.

Friedman, J.H., 2001. Greedy function approximation: a gradient boosting machine. Ann. Stat. 29, 1189–1232.

Gabrys, B., Bargiela, A., 2000. General fuzzy min–max neural network for clustering and classification. IEEE Trans. Neural Network. 11 (3), 769–783.

Garðarsson, G.Ö., Boem, F., Toni, L., 2022. Graph-based learning for leak detection and localisation in water distribution networks. IFAC-PapersOnLine 55 (6), 661–666. https://doi.org/10.1016/j.ifacol.2022.07.203. . ISSN 2405-8963.

Ghaedi, A.M., Vafaei, A., 2017. Applications of artificial neural networks for adsorption removal of dyes from aqueous solution: a review. Adv. Colloid Interface Sci. 245, 20–39. https://doi.org/10.1016/j.cis.2017.04.015.

Gharehbaghi, A., Ghasemlounia, R., Ahmadi, F., Albaji, M., 2022. Groundwater level prediction with meteorologically sensitive Gated Recurrent Unit (GRU) neural networks. J. Hydrol. 612 (Part C), 128262. https://doi.org/10.1016/j.jhydrol.2022.128262. . ISSN 0022-1694.

Ghojogh, B., Ghodsi, A., Karray, F., Crowley, M., 2021. Uniform Manifold Approximation and Projection (UMAP) and its Variants: Tutorial and Survey. ArXi Abs/2109. 02508.

Ghosh, A., Adhikary, P.P., Bera, B., Bhunia, G.S., 2022. Assessment of groundwater potential zone using MCDA and AHP techniques: case study from a tropical river basin of India. Appl. Water Sci. 12, 1–22. https://doi.org/10.1007/s13201-021-01548-5.

Giles, A.B., Davies, J.E., Ren, K., Kelaher, B., 2021. A deep learning algorithm to detect and classify sun glint from high-resolution aerial imagery over shallow marine environments. ISPRS J. Photogrammetry Remote Sens. 181, 20–26. https://doi.org/10.1016/j.isprsjprs.2021.09.004. . ISSN 0924-2716.

Gires, A., Giangola-Murzyn, A., Abbes, J.B., Tchiguirinskaia, I., Schertzer, D., Lovejoy, S., 2015. Impacts of small-scale rainfall variability in urban areas: a case study with 1D and 1D/2D hydrological models in a multifractal framework. Urban Water J. 12 (8), 607–617.

Gong, N., Denoeux, T., Bertrand-Krajewski, J.L., 1996. Neural networks for solid transport modelling in sewer systems during storm events. Water Sci. Technol. 33 (9), 85–92. https://doi.org/10.2166/wst.1996.0183.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y., 2014. Generative adversarial nets. In: Proceedings of the International Conference on Neural Information Processing Systems (NIPS 2014). pp. 2672–2680.

Goodfellow, I., Bengio, Y., Courville, A., 2016. Deep Learning. The MIT Press, Cambridge, Massachusetts.

Granata, F., Di Nunno, F., de Marinis, G., 2022. Stacked machine learning algorithms and bidirectional long short-term memory networks for multi-step ahead streamflow forecasting: a comparative study. J. Hydrol. 613 (Part A), 128431. https://doi.org/10.1016/j.jhydrol.2022.128431. . ISSN 0022-1694.

Guénard, G., Morin, J., Matte, P., Secretan, Y., Valiquette, E., Mingelbier, M., 2020. Deep learning habitat modeling for moving organisms in rapidly changing estuarine environments: a case of two fishes. Estuar. Coast Shelf Sci. 238, 106713. https://doi.org/10.1016/j.ecss.2020.106713.

Guo, Y.M., Liu, Y.G., Zeng, G.M., Hu, X.J., Xu, W.H., Liu, Y.Q., Liu, S.M., Sun, H.S., Ye, J., Huang, H.J., 2014. An integrated treatment of domestic wastewater using sequencing batch biofilm reactor combined with vertical flow constructed wetland and its artificial neural network simulation study. Ecol. Eng. 64, 18–26. https://doi.org/10.1016/j.ecoleng.2013.12.040.

Guo, H., Jeong, K., Lim, J., Jo, J., Kim, Y.M., Park, J., Kim, J.H., Cho, K.H., 2015. Prediction of effluent concentration in a wastewater treatment plant using machine learning models. J. Environ. Sci. 32, 90–101. https://doi.org/10.1016/j.jes.2015.01.007.

Guzman, S.M., Paz, J.O., Tagert, M.L.M., 2017. The Use of NARX Neural Networks to Forecast Daily Groundwater Levels, vol. 31. Water Resources Management, pp. 1591–1603. https://doi.org/10.1007/s11269-017-1598-5.

Hadiyan, P.P., Moeini, R., Ehsanzadeh, E., 2020. Application of static and dynamic artificial neural networks for forecasting inflow discharges, case study: Sefidroud Dam reservoir. Sustain. Comput.: Informatic. Syst. 27. https://doi.org/10.1016/j.suscom.2020.100401.

Hammid, A.T., Bin Sulaiman, M.H., Abdalla, A.N., 2018. Prediction of small hydropower plant power production in Himreen Lake dam (HLD) using artificial neural network. Alex. Eng. J. 57 (1), 211–221. https://doi.org/10.1016/j.aej.2016.12.011.

Harappa, 2020. Lothal: sanitary drainage at the acropolis. Available at: https://www.harappa.com/lothal/. (Accessed 1 September 2020).

Hartigan, J.A., Wong, M.A., 1979. Algorithm AS 136: a k-means clustering algorithm. J. Roy. Stat. Soc. C 28, 100–108.

Hastie, T., Tibshirani, R., Friedman, J.H., 2009. Chapter 10. Boosting and additive tress, The Elements of Statistical Learning, second ed. Springer, New York, pp. 337–384.

He, H., Lui, L., Zhu, X., 2022. Optimization of extreme learning machine model with biological heuristic algorithms to estimate daily reference evapotranspiration in Hetao Irrigation District of China. Eng. Appl. Comput. Fluid Mech. 16 (1), 1939–1956. https://doi.org/10.1080/19942060.2022.2125442.

Herrera, M., Torgo, L., Izquierdo, J., Pérez-García, R., 2010. Predictive models for forecasting hourly urban water demand. J. Hydrol. 387 (1–2), 141–150. https://doi.org/10.1016/j.jhydrol.2010.04.005.

Hikouei, I.S., Eshleman, K.N., Saharjo, B.H., Graham, L.L.B., Applegate, G., Cochrane, M.A., 2023. Using machine learning algorithms to predict groundwater levels in Indonesian tropical peatlands. Sci. Total Environ. 857 (3), 159701. https://doi.org/10.1016/j.scitotenv.2022.159701. . ISSN 0048-9697.

Hinton, G., 2009. Deep belief networks. Scholarpedia 4, 5947.

History, Water, 2020. Water-related infrastructure in medieval London. Available at: http://www.waterhistory.org/histories/london/. 14/09/20.

Hochreiter, S., Schmidhuber, J., 1997. Long short-term memory. Neural Comput. 9, 1735–1780.

Hoerl, A.E., Kennard, W.R., 1970. Ridge Regression: biased estimation for nonorthogonal problems. Technometrics 12, 55–67.

Hopfield, J.J., 1982. Neural networks and physical systems with emergent collective computational abilities. Proc. Natl. Acad. Sci. USA 79, 2554–2558.

Hosseiny, H., 2021. A deep learning model for predicting river flood depth and extent. Environ. Model. Software 145, 105186. https://doi.org/10.1016/j.envsoft.2021.105186. . ISSN 1364-8152.

Hsu, N.S., Huang, C.L., Wei, C.C., 2013. Intelligent real-time operation of a pumping station for an urban drainage system. J. Hydrol. 489, 85–97. https://doi.org/10.1016/j.jhydrol.2013.02.047.

Hu, X., Han, Y., Yu, B., Geng, Z., Fan, J., 2021. Novel leakage detection and water loss management of urban water supply network using multiscale neural networks. J. Clean. Prod. 278, 123611. https://doi.org/10.1016/j.jclepro.2020.123611.

Huang, W., Murray, C., Kraus, N., Rosati, J., 2003. Development of a regional neural network for coastal water level predictions. Ocean Eng. 30 (17), 2275–2295. https://doi.org/10.1016/S0029-8018(03)00083-0.

Hunt, K.M.R., Matthews, G.R., Pappenberger, F., Prudhomme, C., 2022. Using a long short-term memory (LSTM) neural network to boost river streamflow forecasts over the western United States, Hydrol. Earth Syst. Sci. 26, 5449–5472. https://doi.org/10.5194/hess-26-5449-2022.

Ibrahim, A., Ismail, A., Juahir, H., Iliyasu, A.B., Wailare, B.T., Mukhtar, M., Aminu, H., 2023. Water quality modelling using principal component analysis and artificial neural network. Mar. Pollut. Bull. 187, 114493. https://doi.org/10.1016/j.marpolbul.2022.114493. . ISSN 0025-326X.

Ilhan, A., 2023. Forecasting of volumetric flow rate of Ergene river using machine learning. Eng. Appl. Artif. Intell. 121, 105983. https://doi.org/10.1016/j.engappai.2023.105983. . ISSN 0952-1976.

International Hydropower Association, 2020. 2020 hydropower Status report. Available at: https://www.hydropower.org/statusreport. 01/09/20.

Interreg Central Europe, 2020. Water loss. Available at: https://www.interreg-central.eu/Content.Node/Digital-Learning-Resources/03-Water-Loss.pdf. 23/07/20.

Jalal, A., Salman, A., Mian, A., Shortis, M., Shafait, F., 2020. Fish detection and species classification in underwater environments using deep learning with temporal information. Ecol. Inf. 57, 101088. https://doi.org/10.1016/j.ecoinf.2020.101088.

Janner, M., Li, Q., Levine, S., 2021. 'Offline reinforcement learning as one big sequence modeling problem', advances in neural information processing systems. Curran Associates, Inc. 34, 1273–1286.

Jolliffe, I.T., 2002. Principal Component Analysis, second ed. Springer.

Jouanneau, S., Recoules, L., Durand, M.J., Boukabache, A., Picot, V., Primault, Y., Lakel, A., Sengelin, M., Barillon, B., Thouand, G., 2014. Methods for assessing biochemical oxygen demand (BOD): a review. Water Res. 49, 62–82. https://doi.org/10.1016/j.watres.2013.10.066.

Kaelbling, L.P., Littman, M.L., Moore, A.W., 1996. Reinforcement learning: a survey. J. Artif. Intell. Res. 4, 237–285.

Karimi, B., Mohammadi, P., Sanikhani, H., Salih, S.Q., Yaseen, Z.M., 2020. Modeling wetted areas of moisture bulb for drip irrigation systems: an enhanced empirical model and artificial neural network. Comput. Electron. Agric. 178, 105767. https://doi.org/10.1016/j.compag.2020.105767.

Kaufman, L., Rousseeuw, P.J., 1990. Partitioning Around Medoids (Program PAM). Wiley Series in Probability and Statistics. John Wiley & Sons, Inc., Hoboken, NJ, USA, pp. 68–125.

Kavousian, A., Rajagopal, R., Fischer, M., 2013. Determinants of residential electricity consumption: using smart meter data to examine the effect of climate, building characteristics, appliance stock, and occupants' behaviour. Energy 55, 184–194. https://doi.org/10.1016/j.energy.2013.03.086.

Kayhomayoon, Z., Ghordoyee-Milan, S., Jaafari, A., Arya-Azar, N., Melesse, A.M., Moghaddam, H.K., 2022. How does a combination of numerical modeling, clustering, artificial intelligence, and evolutionary algorithms perform to predict regional groundwater levels? Comput. Electron. Agric. 203, 107482. https://doi.org/10.1016/j.compag.2022.107482. . ISSN 0168-1699.

Kim, C.M., Parnichkun, M., 2017. Prediction of settled water turbidity and optimal coagulant dosage in drinking water treatment plant using a hybrid model of k-means clustering and adaptive neuro-fuzzy inference system. Appl. Water Sci. 7 (7), 3885–3902.

Kim, J., Lee, T., Seo, D., 2017. Algal bloom prediction of the lower Han River, Korea using the EFDC hydrodynamic and water quality model. Ecol. Model. 366, 27–36. https://doi.org/10.1016/j.ecolmodel.2017.10.015.

Kizza, C., Pan, S., Bockelman-Evans, B., Babatunde, A., 2020. Predicting pollutant removal in constructed wetlands using artificial neural networks (ANNs). Water Sci. Eng. 13 (1), 14–23. https://doi.org/10.1016/j.wse.2020.03.005.

Kochhar, A., Singh, H., Sahoo, S., Litoria, P.K., Pateriya, B., 2021. Prediction and forecast of pre-monsoon and post-monsoon groundwater level: using deep learning and statistical modelling. Model. Earth Syst. Environ. 8, 2317–2329. https://doi.org/10.1007/s40808-021-01235-z.

Kramer, M.A., 1991. Nonlinear principal component analysis using autoassociative neural networks. AIChE J. 37, 233–243.

Le Cun, Y., Boser, B., Denker, J.S., Henderson, D., Howard, R.E., Hubbard, W., Jackel, L.D., 1990. Handwritten digit recognition with a back-propagation network. In: Proc. Advances in Neural Information Processing Systems. pp. 396–404.

Le Cun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. Nature 521, 436–444.

Le, X.-H., Nguyen, D.-H., Jung, S., Yeon, M., Lee, G., 2021. Comparison of deep learning techniques for river streamflow forecasting. IEEE Access 9, 71805–71820. https://doi.org/10.1109/ACCESS.2021.3077703.

Lee, D.D., Seung, H.S., 2001. Algorithms for non-negative matrix factorization. In: Advances in Neural Information Processing Systems 13: Proceedings of the 2000 Conference. MIT Press, pp. 556–562.

Léger, P., Leclerc, M., 2007. Hydrostatic, temperature, time-displacement model for concrete dams. J. Eng. Mech. 133 (3), 267–277.

Lewis, N.D.C., 2016. Deep Learning Made Easy with R: a Gentle Introduction for Data

Science. CreateSpace Independent Publishing Platform.

Li, X., Xu, W., Ren, M., Jiang, Y., Fu, G., 2022. Hybrid CNN-LSTM models for river flow prediction. Water Supply 22 (5), 4902–4919. https://doi.org/10.2166/ws.2022.170.

Li, Y.L., Gao, Q., Li, D.H., 2018. A gray RBF model improved by genetic algorithm for electrical power forecasting. In: Chinese Control and Decision Conference. CCDC, pp. 5065–5070.

Li, S., Kazemi, H., Rockaway, T.D., 2019. Performance assessment of stormwater GI practices using artificial neural networks. Sci. Total Environ. 651 (2), 2811–2819. https://doi.org/10.1016/j.scitotenv.2018.10.155.

Liu, Q., Gui, D., Zhang, L., Niu, J., Dai, H., Wei, G., Hu, B.X., 2022. Simulation of regional groundwater levels in arid regions using interpretable machine learning models. Sci. Total Environ. 831 (2022), 154902. https://doi.org/10.1016/j.scitotenv.2022.154902. . ISSN 0048-9697.

Loke, E., Warnaars, E.A., Jacobsen, P., Nelen, F., do Céu Almeida, M., 1997. Artificial neural networks as a tool in urban storm drainage. Water Sci. Technol. 36 (8–9), 101–109. https://doi.org/10.2166/wst.1997.0651.

Löwe, R., Böhm, J., Jensen, D.G., Leandro, J., Rasmussen, S.H., 2021. U-FLOOD – topographic deep learning for predicting urban pluvial flood water depth. J. Hydrol. 603 (Part A), 126898. https://doi.org/10.1016/j.jhydrol.2021.126898. . ISSN 0022-1694.

Lucas, P.O., Alves, M.A., Silva, P.C.L., Guimarães, F.G., 2020. Reference evapotranspiration time series forecasting with ensemble of convolutional neural networks. Comput. Electron. Agric. 177, 105700. https://doi.org/10.1016/j.compag.2020.105700.

Ma, J., Ding, Y., Cheng, J.C.P., Jiang, F., Xu, Z., 2020. Soft Detection of 5-day BOD with Sparse Matrix in City Harbor Water Using Deep Learning Techniques, vol. 170. Water Research, 115350. https://doi.org/10.1016/j.watres.2019.115350.

Ma, X., Hu, H., Ren, Y., 2023. A hybrid deep learning model based on feature capture of water level influencing factors and prediction error correction for water level prediction of cascade hydropower stations under multiple time scales. J. Hydrol. 617 (Part C), 129044. https://doi.org/10.1016/j.jhydrol.2022.129044. . ISSN 0022-1694.

MacQueen, J.B., 1967. Some methods for classification and analysis of multivariate observations. In: Proceedings of 5th Berkeley Symposium on Mathematical Statistics and Probability, vol. 1. University of California Press, pp. 281–297.

Maroufpoor, S., Maroufpoor, E., Bozorg-Haddad, O., Shiri, J., 2019a. Soil moisture simulation using hybrid artificial intelligent model: hybridisation of adaptive neuro fuzzy inference system with grey wolf optimiser algorithm. J. Hydrol. 544–556. https://doi.org/10.1016/j.jhydrol.2019.05.045.

Maroufpoor, S., Shiri, J., Maroufpoor, E., 2019b. Modeling the sprinkler water distribution uniformity by data-driven methods based on effective variables. Agric. Water Manag. 215, 62–73. https://doi.org/10.1016/j.agwat.2019.01.008.

Martins, V.S., Kaleita, A.L., Gelder, B.K., Nagel, G.W., Maciel, D.A., 2020. Deep neural network for complex open-water wetland mapping using high-resolution WorldView-3 and airborne LiDAR data. Int. J. Appl. Earth Obs. Geoinf. 93, 102215. https://doi.org/10.1016/j.jag.2020.102215.

Mattar, M.A., Alazba, A.A., El-Abedin, T.K.Z., 2015. Forecasting furrow irrigation infiltration using artificial neural networks. Agric. Water Manag. 148, 63–71. https://doi.org/10.1016/j.agwat.2014.09.015.

Maugis, C., Celeux, G., Martin-Magniette, M.-L., 2009. Variable selection for clustering with Gaussian mixture models. Biometrics 65, 701–709.

Mehedi, M.A.A., Khosravi, M., Yazdan, M.M.S., Shabanian, H., 2022. Exploring temporal dynamics of river discharge using univariate long short-term memory (LSTM) recurrent neural network at east branch of Delaware river. Hydrology 9, 202. https://doi.org/10.3390/hydrology9110202.

Meng, L., Feng, Q., Lui, P., Ding, E., 2014. Research on Key Technologies of Coal Mine Groundwater Perception Based on IoT. 12th International Mine Water Association, pp. 437–440.

Mnih, V., et al., 2015. Human-level control through deep reinforcement learning. Nature 518, 529–533.

Mohapatra, J.B., Jha, P., Jha, M.K., Biswal, S., 2021. Efficacy of machine learning techniques in predicting groundwater fluctuations in agro-ecological zones of India. Sci. Total Environ. 785, 147319. https://doi.org/10.1016/j.scitotenv.2021.147319. . ISSN 0048-9697.

Mouatadid, S., Adamowski, J., 2017. Using extreme learning machines for short-term urban water demand forecasting. Urban Water J. 14 (6), 630–638. https://doi.org/10.1080/1573062X.2016.1236133.

Mouatadid, S., Adamowski, J.F., Tiwari, M.K., Quilty, J.M., 2019. Coupling the maximum overlap discrete wavelet transform and long short-term memory networks for irrigation flow forecasting. Agric. Water Manag. 219, 72–85. https://doi.org/10.1016/j.agwat.2019.03.045.

Mullapudi, A., Lewis, M.J., Gruden, C.L., Kerkez, B., 2020. Deep reinforcement learning for the real time control of stormwater systems. Adv. Water Resour. 140, 103600. https://doi.org/10.1016/j.advwatres.2020.103600.

Najafzadeh, M., Zeinolabedini, M., 2019. Prognostication of waste water treatment plant performance using efficient soft computing models: an environmental evaluation. Measurement 138, 690–701. https://doi.org/10.1016/j.measurement.2019.02.014.

Nandi, I., Srivastava, P.K., Shah, K., 2017. Floodplain mapping through support vector machine and optical/infrared images from Landsat 8 OLI/TIRS sensors: case study from Varanasi. Water Resour. Manag. 31 (4), 1157–1171.

Narendran, S., Pradeep, P., Ramesh, M.V., 2017. An Internet of Things (IoT) Based Sustainable Water Management. Global Humanitarian Technology Conference IEEE, pp. 1–6.

Nasseri, M., Moeini, A., Tabesh, M., 2011. Forecasting monthly urban water demand using extended Kalman filter and genetic programming. Expert Syst. Appl. 38 (6), 7387–7395. https://doi.org/10.1016/j.eswa.2010.12.087.

National Biodiversity Network, 2019. State of nature. Available at: https://nbn.org.uk/wp-content/uploads/2019/09/State-of-Nature-2019-UK-full-report.pdf. (Accessed 9 April 2020).

National Geographic, 2020. Freshwater crisis. Available at: https://www.nationalgeographic.com/environment/freshwater/freshwater-crisis/. (Accessed 28 February 2020).

National Thailand, 2019. Dams drying up, drought may drag into 2020. Available at: https://www.nationthailand.com/news/30373918. 23/06/20.

Newhart, K.B., Holloway, R.W., Hering, A.S., Cath, T.Y., 2019. Data-driven Performance Analyses of Wastewater Treatment Plants: A Review, vol. 157. Water Research, pp. 498–513. https://doi.org/10.1016/j.watres.2019.03.030.

Niu, G., Yi, X., Chen, C., Li, X., Han, D., Yan, B., Huang, M., Ying, G., 2020. A novel effluent quality predicting model based on genetic-deep belief network algorithm for cleaner production in a full-scale paper-making wastewater treatment. J. Clean. Prod. 265, 121787. https://doi.org/10.1016/j.jclepro.2020.121787.

Our World in Data, 2020. Fossil fuels. Available at: https://ourworldindata.org/fossil-fuels#licence. 01/08/20.

Pathak, D., Maharjan, R., Maharjan, N., Shrestha, S.R., Timilsina, P., 2021. Evaluation of parameter sensitivity for groundwater potential mapping in the mountainous region of Nepal Himalaya. Groundw. Sustain. Dev. 13, 2–14. https://doi.org/10.1016/j.gsd.2021.100562.

Patra, S.R., Chu, H.-J., Tatas, 2023. Regional groundwater sequential forecasting using global and local LSTM models. J. Hydrol.: Reg. Stud. 47, 101442. https://doi.org/10.1016/j.ejrh.2023.101442. . ISSN 2214-5818.

Peduzzi, P., 2017. Prioritising protection? Nat. Climate Change 7, 625–626.

Pektaşa, A.O., Cigizoglu, H.K., 2013. ANN hybrid model versus ARIMA and ARIMAX models of runoff coefficient. J. Hydrol. 500, 21–36. https://doi.org/10.1016/j.jhydrol.2013.07.020.

Penot, I., Daumas, B., Fabre, J.P., 2005. Monitoring behaviour. Water Power Dam Construct. 57 (24), 27.

Perea, R.G., Poyato, E.C., Montesinos, P., Díaz, J.A.R., 2019. Optimisation of water demand forecasting by artificial intelligence with short data sets. Biosyst. Eng. 177, 56–66. https://doi.org/10.1016/j.biosystemseng.2018.03.011.

Pesantez, J.E., Berglund, E.Z., Kaza, N., 2020. Smart Meters Data for Modeling and Forecasting Water Demand at the User-Level, vol. 125. Environmental Modelling & Software, 104633. https://doi.org/10.1016/j.envsoft.2020.104633.

Pham, Q.B., Kumar, K, M., Di Nunno, F., Elbeltagi, A., Granata, F., Towfiqul Islam, A.R.M., Talukdar, S., Nguyen, X.C., Ahmed, A.N., Anh, D.T., 2022. Groundwater level prediction using machine learning algorithms in a drought-prone area. Neural Comput. Appl. 34, 10751–10773.

Poisson, A., Fernandez, A., Gomez, D.G., Barillé, R., Chorro, B., 2017. Assessment and prediction of evapotranspiration based on scintillometry and meteorological datasets. IntechOpen. https://doi.org/10.5772/intechopen.68538.

Polosukhin, I., Kaiser, L., Gomez, A.N., Jones, L., Uszkoreit, J., Parmar, N., Shazeer, N., Vaswani, A., 2017. Advances in Neural Information Processing Systems, vol. 30. Curran Associates, Inc.

Pudjihartono, N., Fadason, T., Kempa-Liehr, A.W., O'Sullivan, J.M., 2022. A review of feature selection methods for machine learning-based disease risk prediction. Front. Bioinform. 2, 927312.

Pyo, J., Park, L.J., Pachepsky, Y., Baek, S., Kim, K., Cho, K.H., 2020. Using Convolutional Neural Network for Predicting Cyanobacteria Concentrations in River Water, vol. 186. Water Research, 116349. https://doi.org/10.1016/j.watres.2020.116349.

Quinlan, J.R., 1986. Induction of Decision Trees, vol. 1. Machine Learning, pp. 81–106. https://doi.org/10.1007/BF00116251.

Radford, A., Metz, L., Chintala, S., 2015. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks. arXiv preprint arXiv:1511.06434.

Radford, A., Narasimhan, K., Salimans, T., Sutskever, I., 2018. Improving Language understanding by generative pre-training. Available at: https://cdn.openai.com/research-covers/languageunsupervised/language_understanding_paper.pdf. 18/08/23.

Ráduly, B., Gernaey, K.V., Capodaglio, A.G., Mikkelsen, P.S., Henze, M., 2007. Artificial neural networks for rapid WWTP performance evaluation: methodology and case study. Environ. Model. Software 22 (8), 1208–1216. https://doi.org/10.1016/j.envsoft.2006.07.003.

Rahaman, M.M., Thakur, B., Kalra, A., Ahmad, S., 2019. Modeling of GRACE-derived groundwater information in the Colorado River Basin. Hydrol. 6 (1), 19. https://doi.org/10.3390/hydrology6010019.

Rahman, A.T.M.S., Hosono, T., Quilty, J.M., Das, J., Basak, A., 2020. Multiscale groundwater level forecasting: coupling new machine learning approaches with wavelet transforms. Adv. Water Resour. 141, 103595. https://doi.org/10.1016/j.advwatres.2020.103595. . ISSN 0309-1708.

Rajeevan, U., Mishra, B.K., 2020. Sustainable management of the groundwater resource of Jaffna, Sri Lanka with the participation of households: insights from a study on household water consumption and management. Groundw. Sustain. Dev. 10. https://doi.org/10.1016/j.gsd.2019.100280.

Ramayanti, S., Nur, A.S., Syifa, M., Panahi, M., Achmad, A.R., Park, S., Lee, C.W., 2022. Performance comparison of two deep learning models for flood susceptibility map in Beira area, Mozambique. Egyptian J. Rem. Sens. Space Sci. 25 (Issue 4), 1025–1036. https://doi.org/10.1016/j.ejrs.2022.11.003. . ISSN 1110-9823.

Reikard, G., 2009. Forecasting ocean wave energy: tests of time-series models. Ocean Eng. 36 (5), 348–356. https://doi.org/10.1016/j.oceaneng.2009.01.003.

Ren, T., Liu, X., Niu, J., Lei, X., Zhang, Z., 2020. Real-time water level prediction of cascaded channels based on multilayer perception and recurrent neural network. J. Hydrol. 585, 124783. https://doi.org/10.1016/j.jhydrol.2020.124783.

Ren, Q., Li, M., Li, H., Shen, Y., 2021. A novel deep learning prediction model for concrete dam displacements using interpretable mixed attention mechanism. Adv. Eng. Inf. 50,

101407. https://doi.org/10.1016/j.aei.2021.101407. . ISSN 1474-0346.
Rentschler, J., Salhab, M., 2020. People in harm's way: flood exposure and poverty in 189 countries. In: Policy Research Working Paper. No. 9447. The World Bank, Washington DC.
Ridolfi, E., Servili, F., Magini, R., Napolitano, F., Russo, F., Alfonso, L., 2014. Artificial neural networks and entropy-based methods to determine pressure distribution in water distribution systems. Procedia Eng. 89, 648–655. https://doi.org/10.1016/j.proeng.2014.11.490.
Rjelly, Y.A., Abbas, O., Sadek, M., Shahrour, I., Chehade, F.H., 2018. Model predictive control for optimising the operation of urban drainage systems. J. Hydrol. 566, 558–565. https://doi.org/10.1016/j.jhydrol.2018.09.044.
Rohde, M.M., Biswas, T., Housman, I.W., Campbell, L.S., Klausmeyer, K.R., Howard, J.K., 2021. A machine learning approach to predict groundwater levels in California reveals ecosystems at risk. Front. Earth Sci. 9. https://doi.org/10.3389/feart.2021.784499. . ISSN = 2296-6463.
Romano, M., Kapelan, Z., 2014. Adaptive Water Demand Forecasting for Near Real-Time Management of Smart Water Distribution Systems, vol. 60. Environmental Modelling & Software, pp. 265–276. https://doi.org/10.1016/j.envsoft.2014.06.016.
Rummery, G.A., Niranjan, M., 1994. On-line Q-Learning Using Connectionist Systems. Department of Engineering, University of Cambridge, Cambridge.
Rutkowski, T.A., Prokopiuk, F., 2018. Identification of the contamination source location in the drinking water distribution system based on the neural network classifier. IFAC-PapersOnLine 51 (24), 15–22. https://doi.org/10.1016/j.ifacol.2018.09.523.
Salakhutdinov, R., Hinton, G., 2009. Deep Boltzmann machines. In: Proceedings of the Twelfth International Conference on Artificial Intelligence and Statistics, vol. 5. PMLR, pp. 448–455.
Salloom, T., Kaynak, O., He, W., 2021. A novel deep neural network architecture for real-time water demand forecasting. J. Hydrol. 599, 126353. https://doi.org/10.1016/j.jhydrol.2021.126353. . ISSN 0022-1694.
Salloom, T., Kaynak, O., Yu, X., He, W., 2022. Proportional integral derivative booster for neural networks-based time-series prediction: case of water demand prediction. Eng. Appl. Artif. Intell. 108, 104570. https://doi.org/10.1016/j.engappai.2021.104570. . ISSN 0952-1976.
Salvadore, E., Bronders, J., Batelaan, O., 2015. Hydrological modelling of urbanised catchments: a review and future directions. J. Hydrol. 529 (1), 62–81.
Sang-Soo, Baek, Pyo, Jongcheol, Chun, Jong Ahn, 2020. Prediction of water level and water quality using a CNN-LSTM combined deep learning approach. Water 12, 3399.
Schmidhuber, J., 2015. Deep learning in neural networks: an overview. Neural Network. 61, 85–117.
Schulman, J., Wolski, F., Dhariwal, P., Radford, A., Klimov, O., 2017. Proximal Policy Optimization Algorithms. arXiv:1707.06347.
Science Daily, 2020. Water resources. Available at: https://www.sciencedaily.com/terms/water_resources.htm. (Accessed 1 September 2020).
Shahra, E.Q., Wu, W., Romano, M., 2019. Considerations on the deployment of heterogeneous IoT devices for smart water networks. In: 2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation, Leicester, UK, pp. 791–796.
Shakya, C.M., Bhattacharjya, R.K., Dadhich, S., 2022. Groundwater level prediction with machine learning for the Vidisha district, a semi-arid region of Central India. Groundwater Sustain. Develop. 19, 100825. https://doi.org/10.1016/j.gsd.2022.100825. . ISSN 2352-801X.
Sharafati, A., Asadollah, S.B.H.S., Neshat, A., 2020. A new artificial intelligence strategy for predicting the groundwater level over the Rafsanjan aquifer in Iran. J. Hydrol. 591, 125468. https://doi.org/10.1016/j.jhydrol.2020.125468. . ISSN 0022-1694.
Sharma, A., 2018. Guided Stochastic Gradient Descent Algorithm for Inconsistent Datasets, vol. 73. Applied Soft Computing, pp. 1068–1080. https://doi.org/10.1016/j.asoc.2018.09.038.
Sherrington, D., Kirkpatrick, S., 1975. Solvable model of a spin-glass. Phys. Rev. Lett. 35, 1792–1796.
Shi, S., Xu, G., 2018. Novel performance prediction model of a biofilm system treating domestic wastewater based on stacked denoising auto-encoders deep learning network. Chem. Eng. J. 347, 280–290. https://doi.org/10.1016/j.cej.2018.04.087.
Sonic, L.G., 2020. Cyanobacterial blooms: causes, dangers and treatment. Available at: https://www.lgsonic.com/cyanobacterial-blooms/. (Accessed 1 September 2020).
Sorkhabi, O.M., Shadmanfar, B., Al-Amidi, M.M., 2023. Deep learning of sea-level variability and flood for coastal city resilience. City and Environ. Interact. 17, 100098. https://doi.org/10.1016/j.cacint.2022.100098. . ISSN 2590-2520.
Steinwart, I., Christmann, A., 2008. Support Vector Machines. Springer.
Su, Y., Ni, C., Li, W., Lee, I., Lin, C., 2020. Applying Deep Learning Algorithms to Enhance Simulations of Large-Scale Groundwater Flow in IoTs. Applied Soft Computing, p. 92. https://doi.org/10.1016/j.asoc.2020.106298.
Sun, J., Hu, Li, Li, D., Sun, K., Yang, Z., 2022. Data-driven models for accurate groundwater level prediction and their practical significance in groundwater management. J. Hydrol. 608, 127630. https://doi.org/10.1016/j.jhydrol.2022.127630. . ISSN 0022-1694.
Sung, M., Yu, S.C., Girdhar, Y., 2020. Vision based real-time fish detection using convolutional neural network. OCEANS 2017-Aberdeen 1–6. . IEEE.
Sutton, R.S., McAllester, D., Singh, S., Mansour, Y., 2000. Policy gradient methods for reinforcement learning with function approximation. Adv. Neural Inf. Process. Syst. 12, 1057–1063.
Tao, H., Hameed, M.M., Marhoon, H.A., Zounemat-Kermani, M., Heddam, S., Kim, S., Sulaiman, S.O., Tan, M.L., Sa'adi, Z., Mehr, A.D., Allawi, M.F., Abba, S.I., Zain, J.S., Falah, M.W., Jamei, M., Bokde, N.D., Bayatvarkeshi, M., Al-Mukhtar, M., Bhagat, S.K., Tiyasha, T., Khedher, K.M., Al-Ansari, N., Shahid, S., Yaseen, Z.M., 2022. Groundwater level prediction using machine learning models: a comprehensive review. Neurocomputing 489, 271–308. https://doi.org/10.1016/j.neucom.2022.03.014. . ISSN 0925-2312.
Tata, Howard, 2016. A history of dams: from ancient times to today. Available at: https://tataandhoward.com/2016/05/a-history-of-dams-from-ancient-times-to-today/. (Accessed 1 February 2020).
Teimoori, S., Olya, M.H., Miller, C.J., 2023. Groundwater level monitoring network design with machine learning methods. J. Hydrol. 625 (Part B), 130145. https://doi.org/10.1016/j.jhydrol.2023.130145. . ISSN 0022-1694.
Tenenbaum, J.B., Silva, V.d., Langford, J.C., 2000. A global geometric framework for nonlinear dimensionality reduction. Science 290, 2319–2323.
Teng, J., Jakeman, A.J., Vaze, J., Croke, B.F.W., Dutta, D., Kim, S., 2017. Flood Inundation Modelling: a Review of Methods, Recent Advances and Uncertainty Analysis, vol. 90. Environmental Modelling & Software, pp. 201–216.
Tibshirani, R., 1996. Regression shrinkage and selection via the Lasso. J. Roy. Stat. Soc. B 58, 267–288.
Tran, D.H., Ng, A.W.N., Perera, B.J.C., 2007. Neural networks deterioration models for serviceability condition of buried stormwater pipes. Eng. Appl. Artif. Intell. 20 (8), 1144–1151.
Triguero, I., García, S., Herrera, F., 2015. Self-labeled techniques for semi-supervised learning: taxonomy, software and empirical study. Knowl. Inf. Syst. 42, 245–284.
Truong, V.H., Ly, Q.V., Le, V.C., Vu, T.B., Le, T.T.T., Tran, T.T., Goethals, P., 2021. Machine learning-based method for forecasting water levels in irrigation and drainage systems. Environ. Technol. Innovat. 23, 101762. https://doi.org/10.1016/j.eti.2021.101762. . ISSN 2352-1864.
United Nations, 2015. The human cost of weather-related disasters. Available at: https://www.unisdr.org/2015/docs/climatechange/COP21_WeatherDisastersReport_2015_FINAL.pdf. 06/09/20.
United Nations Educational, 2017. The united Nations world water development report. Available at: Scientific and Cultural Organization. http://www.unesco.org/new/en/natural-sciences/environment/water/wwap/wwdr/14/09/20.
United Nations Environment Programme, 2016. A snapshot of the world's water quality: towards a global assessment. Available at: https://uneplive.unep.org/media/docs/assessments/unep_wwqa_report_web.pdf. 12/09/20.
United Nations International Children's Emergency Fund, 2015. Progress on Sanitation and Drinking Water: 2015 Update and MDG Assessment. Available at: https://www.unicef.org/publications/index_82419.html. 14/09/20.
United Nations Water, 2020. Water scarcity. Available at: https://www.unwater.org/water-facts/scarcity/. 01/09/20.
Van Engelen, J.E., Hoos, H.H., 2020. A survey on semi-supervised learning. Mach. Learn. 109, 373–440.
Van Thieu, N., Barma, S.D., Lam, T.V., Kisi, O., Mahesha, A., 2023. Groundwater level modeling using augmented artificial ecosystem optimization. J. Hydrol. 617 (Part C), 129034. https://doi.org/10.1016/j.jhydrol.2022.129034. . ISSN 0022-1694.
Vapnik, V.N., 2013. The Nature of Statistical Learning Theory. Springer-Verlag, New York.
Vincent, P., Larochelle, H., 2010. Stacked denoising autoencoders: learning useful representations in a deep network with a local denoising criterion. J. Mach. Learn. Res. 11, 3371–3408.
Wang, Y., Liu, J., Han, Y., 2020. Production capacity prediction of hydropower industries for energy optimisation: evidence based on novel extreme learning machine integrating Monte Carlo. J. Clean. Prod. 272, 122824. https://doi.org/10.1016/j.jclepro.2020.122824.
Wang, G.C., Zhang, Q., Band, S.S., Dehghani, M., Chau, K.W., Tho, Q.T., Zhu, S., Samadianfard, S., Mosavi, A., 2022. Monthly and seasonal hydrological drought forecasting using multiple extreme learning machine models. Eng. Appl. Comput. Fluid Mech. 16 (1), 1364–1381. https://doi.org/10.1080/19942060.2022.2089732.
Wang, J., Wang, Xu, Khu, S.T., 2023. A Decomposition-based Multi-model and Multi-parameter ensemble forecast framework for monthly streamflow forecasting. J. Hydrol. 618, 129083. https://doi.org/10.1016/j.jhydrol.2023.129083. . ISSN 0022-1694.
Ward, P.J., Jongman, B., Aerts, J.C.J.H., Bates, P.D., Botzen, W.J.W., Loaiza, A.D., Hallegate, S., Kind, J.M., Kwadijk, J., Scussolini, P., Winsemius, H.C., 2017. A global framework for future costs and benefits of river-flood protection in urban areas. Nat. Climate Change 7, 642–646.
Watkins, C., 1992. Q-learning. Mach. Learn. 8, 279–292.
Wei, A., Li, X., Yan, L., Wang, Z., Yu, X., 2023. Machine learning models combined with wavelet transform and phase space reconstruction for groundwater level forecasting. Comput. Geosci. 177, 105386. https://doi.org/10.1016/j.cageo.2023.105386. . ISSN 0098-3004.
Welling, M., Kingma, D.P., 2019. An introduction to variational autoencoders. Foundat. Trend. Mach. Learn. 12, 307–392.
Wrobel, A., 1984. On Markovian decision models with a finite skeleton. Math. Methods Oper. Res. 28, 17–27.
Wu, G., Xu, Z., 2011. Prediction of algal blooming using EFDC model: case study in the Daoxiang Lake. Ecol. Model. 222 (6), 1245–1252. https://doi.org/10.1016/j.ecolmodel.2010.12.021.
Wu, J., Wang, Z., Dong, L., 2021. Prediction and analysis of water resources demand in Taiyuan City based on principal component analysis and BP neural network. AQUA – Water Infrastruct., Ecosyst. Soc. 70 (8). https://doi.org/10.2166/aqua.2021.205. . 1272-1268.
Wu, Z., Lu, C., Sun, Q., Lu, W., He, X., Qin, T., Yan, L., Wu, C., 2023. Predicting groundwater level based on machine learning: a case study of the hebei plain. Water 15 (4), 823. https://doi.org/10.3390/w15040823.
Wunsch, A., Liesch, T., Broda, S., 2022. Deep learning shows declining groundwater levels in Germany until 2100 due to climate change. Nat. Commun. 13, 1221. https://doi.org/10.1038/s41467-022-28770-2.

Xu, W., Jiang, Y., Zhang, X., Li, Y., Zhang, R., Fu, G., 2020a. Using long short-term memory networks for river flow prediction. Nord. Hydrol 51 (6), 1358–1376. https://doi.org/10.2166/nh.2020.026.

Xu, C., Xu, Z., Yang, Z., 2020b. Reservoir operation optimisation for balancing hydropower generation and biodiversity conservation in a downstream wetland. J. Clean. Prod. 245, 118885. https://doi.org/10.1016/j.jclepro.2019.118885.

Yadav, B., Gupta, P.K., Patidar, N., Himanshu, S.K., 2020. Ensemble modelling framework for groundwater level prediction in urban areas of India. Sci. Total Environ. 712, 135539. https://doi.org/10.1016/j.scitotenv.2019.135539. . ISSN 0048-9697.

Yan, J., Jia, S., Lv, A., Zhu, W., 2019. Water resources assessment of China's transboundary river basins using a machine learning approach. Water Resour. Res. 55, 632–655. https://doi.org/10.1029/2018WR023044.

Yang, S., Yang, D., Chen, J., Zhao, B., 2019. Real-time reservoir operation using recurrent neural networks and inflow forecast from a distributed hydrological model. J. Hydrol. 579, 124229. https://doi.org/10.1016/j.jhydrol.2019.124229.

Yang, B., Xiao, Z., Meng, Q., Yuan, Y., Wang, W., Wang, H., Wang, Y., Feng, X., 2023. Deep learning-based prediction of effluent quality of a constructed wetland. Environ. Sci. Ecotech. 13, 100207. https://doi.org/10.1016/j.ese.2022.100207. . ISSN 2666-4984.

Yin, W., Fan, Z., Tangdamrongsub, N., Hu, L., Zhang, M., 2021. Comparison of physical and data-driven models to forecast groundwater level changes with the inclusion of GRACE – a case study over the state of Victoria, Australia. J. Hydrol. 602, 126735. https://doi.org/10.1016/j.jhydrol.2021.126735. . ISSN 0022-1694.

Yu, Y., Qu, Y., 2020. Multi-component spectral detection based on neural network in water quality inspection. Optik 217, 164915. https://doi.org/10.1016/j.ijleo.2020.164915.

Yu, C., Li, Z., Yang, Z., Chen, X., Su, M., 2020. A feedforward neural network based on normalisation and error correction for predicting water resources carrying capacity of a city. Ecol. Indicat. 118. https://doi.org/10.1016/j.ecolind.2020.106724.

Yu, T., Chen, X., Yan, W., Xu, Z., Ye, M., 2023. Leak detection in water distribution systems by classifying vibration signals. Mech. Syst. Signal Process. 185, 109810. https://doi.org/10.1016/j.ymssp.2022.109810. . ISSN 0888-3270.

Zhang, G.P., 2003. Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing 50, 159–175.

Zhang, Y.J., Hu, L.S., 2020. Real time estimation of radionuclides in the receiving water of an inland nuclear power plant based on difference gated neural network. Radiat. Phys. Chem. 176, 109019. https://doi.org/10.1016/j.radphyschem.2020.109019.

Zhang, Z.H., Zhao, J.X., Lu, X., Niu, X.Z., 2017. Application of BP neural network based on genetic algorithm in power load forecasting. Comput. Eng. 2 (10), 277–282.

Zhang, D., Hølland, E.S., Lindholm, G., Ratnaweera, H., 2018. Hydraulic modeling and deep learning-based flow forecasting for optimising inter catchment wastewater transfer. J. Hydrol. 567, 792–802. https://doi.org/10.1016/j.jhydrol.2017.11.029.

Zhang, J., Zhang, X., Niu, J., Hu, B.X., Soltanian, M.R., Qui, H., Yang, L., 2019. Prediction of groundwater level in seashore reclaimed land using wavelet and artificial neural network-based hybrid model. J. Hydrol. https://doi.org/10.1016/j.jhydrol.2019.123948.

Zhang, Y., Gao, X., Smith, K., Inial, G., Liu, S., Conil, L.B., Pan, B., 2019. Integrating Water Quality and Operation into Prediction of Water Production in Drinking Water Treatment Plants by Genetic Algorithm Enhanced Artificial Neural Network, vol. 164. Water Research, 114888. https://doi.org/10.1016/j.watres.2019.114888.

Zhang, H., Song, Z., Peng, P., Sun, Y., Ding, Z., Zhang, X., 2020. Research on seepage field of concrete dam foundation based on artificial neural network. Alex. Eng. J. https://doi.org/10.1016/j.aej.2020.03.041.

Zhang, M., Xu, Z., Wang, Y., Zeng, S., Dong, X., 2022. Evaluation of uncertain signals' impact on deep reinforcement learning-based real-time control strategy of urban drainage systems. J. Environ. Manag. 324, 116448. https://doi.org/10.1016/j.jenvman.2022.116448. . ISSN 0301-4797.

Zhang, E., Shao, L., Wang, Y., 2023. Unifying transformer and convolution for dam crack detection. Autom. ConStruct. 147, 104712. https://doi.org/10.1016/j.autcon.2022.104712. . ISSN 0926-5805.

Zhou, Y., 2020. Real-time probabilistic forecasting of river water quality under data missing situation: deep learning plus post-processing techniques. J. Hydrol. 589, 125164. https://doi.org/10.1016/j.jhydrol.2020.125164.

Zhou, S.L., McMahon, T.A., Walton, A., Lewis, J., 2000. Forecasting daily urban water demand: a case study of Melbourne. J. Hydrol. 236 (3–4), 153–164. https://doi.org/10.1016/S0022-1694(00)00287-0.

Zhou, X., Tang, Z., Xu, W., Meng, F., Chu, X., Xin, K., Fu, G., 2019. Deep Learning Identifies Accurate Burst Locations in Water Distribution Networks, vol. 166. Water Research, 115058. https://doi.org/10.1016/j.watres.2019.115058.

Zhu, X., Ghahramani, Z., 2002. Learning from Labeled and Unlabeled Data with Label Propagation, Technical Report CMU-CALD-02-107, School of Computer Science. Carnegie Mellon University.

Zhu, X., Goldberg, A.B., 2009. Introduction to Semi-supervised Learning. Synthesis Lectures on Artificial Intelligence and Machine Learning.

Zhu, J., Jiang, Z., Feng, L., 2022. Improved neural network with least square support vector machine for wastewater treatment process. Chemosphere 308 (1), 136116. https://doi.org/10.1016/j.chemosphere.2022.136116. . ISSN 0045-6535.

Li, L., Yuan, Z., and Gao, Y., 2018. Maximisation of energy absorption for a wave energy converter using the deep machine learning', 'Energy. 165(A), pp. 340-349. doi: 10.1016/j.energy.2018.09.093..