

A Comprehensive Survey of Machine Learning Methodologies with Emphasis in Water Resources Management

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Abstract: This paper offers a comprehensive overview of machine learning (ML) methodologies and algorithms, highlighting their practical applications in the critical domain of water resource management. Environmental issues, such as climate change and ecosystem destruction, pose significant threats to humanity and the planet. Addressing these challenges necessitates sustainable resource management and increased efficiency. Artificial intelligence (AI) and ML technologies present promising solutions in this regard. By harnessing AI and ML, we can collect and analyze vast amounts of data from diverse sources, such as remote sensing, smart sensors, and social media. This enables real-time monitoring and decision making in water resource management. AI applications, including irrigation optimization, water quality monitoring, flood forecasting, and water demand forecasting, enhance agricultural practices, water distribution models, and decision making in desalination plants. Furthermore, AI facilitates data integration, supports decision-making processes, and enhances overall water management sustainability. However, the wider adoption of AI in water resource management faces challenges, such as data heterogeneity, stakeholder education, and high costs. To provide an overview of ML applications in water resource management, this research focuses on core fundamentals, major applications (prediction, clustering, and reinforcement learning), and ongoing issues to offer new insights. More specifically, after the in-depth illustration of the ML algorithmic taxonomy, we provide a comparative mapping of all ML methodologies to specific water management tasks. At the same time, we include a tabulation of such research works along with some concrete, yet compact, descriptions of their objectives at hand. By leveraging ML tools, we can develop sustainable water resource management plans and address the world's water supply concerns effectively.

Keywords: climate change; ecosystem destruction; AI; machine learning (ML); water efficiency; water resources management (WRM); data analysis; prediction; sustainability; decision making; supervised learning; unsupervised learning; classification; regression; clustering



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1. Introduction

The global political agenda has shifted towards urgently addressing environmental issues, particularly climate change, as they pose potential existential threats to humanity and civilization. As we face the destruction of Earth's ecosystem, it is crucial to explore innovative solutions to reverse damage and mitigate adverse effects caused by human activities [1]. The unsustainable depletion of natural resources, driven by population growth and increasing demands for food, water, and energy, is a pressing challenge. Traditional practices in the primary sector lead to overconsumption, environmental pollution, and land desertification. Poor water resource management, including inefficient irrigation and misuse, exacerbates the problem [1,2]. Researchers and environmental governance stakeholders are utilizing emerging technologies like AI, ML, deep learning (DL), IoT, and wireless communications to address critical issues. These technologies enable automated production processes, optimize resource utilization, and minimize human intervention.

High-resolution remote sensing techniques, smart information and communication technologies, and social media platforms have significantly improved data collection, analysis, and decision-making capabilities in weather forecasts, disaster management, and water-energy management [2]. At the same time, the exponential growth of data presents many challenges, making traditional statistical mathematical approaches inadequate. DL algorithms address these challenges by allowing crucial feature extraction and prioritization, optimizing decision-making processes, and reducing reliance on finite resources [2,3]. AI applications have the potential to significantly improve water resource management, especially in urban areas. AI can enhance soil fertility, protect biodiversity, and optimize water management for sustainable agriculture [3]. AI has proven successful in fertilizer and crop selection, and smart irrigation systems using IoT sensors and ML techniques have contributed to freshwater conservation. Artificial neural networks can also optimize soil productivity and resource efficiency [4]. AI applications in water resources management include recording and forecasting water demand, infrastructure installation, water quality monitoring, and disaster prediction. These capabilities can help achieve the Sustainable Development Goals for Water (2030) by facilitating efficient data collection, analysis, and forecasting [5].

This paper utilizes the review papers, firstly, of the ML methodologies as a major research area of AI and computer science as a whole, and then the specialized review papers that explore the ML methodologies that have been applied to water management. The first set covers fundamental algorithms like decision trees, support vector machines, neural networks, clustering algorithms, and supervised classification algorithms within ML (logistic regression, k-nearest neighbor, support vector machines, etc.). The latter set of reviews is dedicated to the impact of a plethora of ML methodologies on analyzing climate change, water resource constraints, population growth, and natural hazards, which forces hydrologists worldwide to adapt and develop strategies to maintain water security. These reviews utilize the rapid growth of hydrologic data repositories and advanced machine learning (ML) models to provide improved assessments in hydrology. As we analyze in the specific subsections of this work, ML models contribute to optimal decision making in water resource management by efficiently modeling nonlinear, erratic, and stochastic behaviors. Furthermore, ML techniques can reduce computational costs, allowing decision makers to transition from physical-based models to ML models for complex problems.

This paper explores the potential of AI and ML applications in optimizing water resources management, particularly in urban areas, to address challenges such as water scarcity, unsustainable consumption, and climate variability through case studies and research findings [6,7]. Addressing these challenges can revolutionize water resource management for a sustainable future. Moreover, this work delves into AI applications in agriculture, irrigation, water quality monitoring, disaster forecasting, and desalination, with a focus on optimizing water consumption and resource allocation to achieve Sustainable Development Goals, while also highlighting the potential of blockchain technology for data security. However, this article can serve as a comprehensive survey of all the ML methodologies used in water management techniques and modeling, rather than a detailed literature review of water-management-related papers, which could include topic modeling, clustering, and taxonomies. AI can revolutionize water management systems by enabling sustainable practices, efficient resource allocation, and a greener future. In a united effort, we aim to harness AI's potential for enhanced water resource management, safeguarding the essential element that sustains all life on Earth.

2. ML Methodologies

Machine learning (ML) in today's world is a critically important tool in our everyday lives [8]. It is essentially a programming technique inspired by AI that enables computers to develop and enhance their learning abilities through data ingestion. The term "machine learning" was first introduced at IBM in 1959 by Arthur Samuel, who gained fame for his work on the game of checkers. He defined machine learning as a broad scientific field of

study that enables computers to approach a problem as a human would, without needing to be explicitly programmed each time. Machine learning is used to teach machines to exploit data efficiently and constructively, making the final results easier to interpret. It involves a set of algorithms and statistical models that, when implemented on computer systems, can perform specific tasks automatically.

According to Ray [9], machine learning is applied in a variety of fields, including robotics, virtual websites (e.g., Google), computer games, pattern recognition, data mining, transportation networks, various predictions (e.g., online fraud detection), environmental predictions, medicine, chatbots for online customer support (BoTs), social media services (such as facial recognition on Facebook), and more.

There are four generalized categories of ML [10]: supervised learning, unsupervised learning, semisupervised learning, and reinforcement learning [11].

2.1. Supervised Learning

Supervised learning essentially involves the desired outcome resulting from actions taken by an instructor or programmer [12]. By using appropriately programmed inputs with labeled data linked to corresponding outputs, it can develop predictive and classification models through a process of iterative learning [13]. This approach is applicable in various social domains, including population evolution and characteristics, as well as predictive indicators like health and water management [14].

Expanding on the earlier explanation, supervised learning requires a dataset that includes labeled examples representing the problem domain. Supervised learning algorithms iteratively adjust their internal parameters to minimize the disparity between predicted and actual labels, effectively capturing the relationships between input features and output labels. This learning paradigm can be categorized into two distinct types: classification, which deals with discrete labels, and regression, where the labels are continuous in nature [15]. In classification, qualitative outputs are used for predictions, while regression employs quantitative outputs for its predictions [16].

2.1.1. Classification

The primary feature of classification is its ability to aid in the construction of predictive models [17]. Classification can be realized using structured or unstructured datasets. The classification algorithm essentially comprehends a training set and, when presented with new data points, assigns a specific function. This results in a reliable function that predicts the class label for registering new data. Some of the terminologies encountered in classification are as follows:

- **Classifiers:** They are algorithms that assign input data to specific classes. They can be categorized into three main types: linear classifiers, nearest-neighbor classifiers, and classification trees [18].
- **Linear classifiers:** Through the linear combination of feature values can make classification decisions [19].
- **Nearest-neighbor classifiers:** Tag data objects that do not share the same label by using the nearest objects from the training set [20].
- **“Brute-force” method classifier:** While not an algorithm, this method exhaustively processes all data and all possible combinatorics to find the best possible classification solution [17]. This method does not involve the intelligent modeling of data mining; instead, it relies solely on computational combinatorics.
- **Classification trees:** A classification tree is a method that offers a descriptive graphical representation of its incremental improvement. To determine the tests, a combination table is utilized, in which class combinations are marked [21].
- **Classification models:** They attempt to make reasonable inferences from the input values provided by the trainer to predict the labels associated with the classes for new data [22].

The types of classification tasks are binary classification, multiclass classification, and multilabel classification.

- **Binary classification:** It is a classification that has two possible outcomes [23]. Basically, it is the process of classifying the data using predefined classes. It can be used in drought prediction [24], **hydrological forecasting** (predicting extreme weather events like heavy rainfall leading to flooding) [25], etc.
- **Multiclass classification:** We have more than two possible outcomes (classes) [26], e.g., it can help automatically classify water quality based on various parameters like chemical composition, turbidity, and biological indicators [27], water demand forecasting [28], flood risk assessment [29], etc.
- **Multilabel classification:** A sample can even be assigned to more than one label [30]. It can be used in **reservoir management** [31], can forecast the streamflow conditions [32], etc.

Linear and nonlinear classification are worthy to be included here as specific approaches or methods used for binary/multiclass/multilabel classifiers. More specifically:

- **Linear classification:** Algorithms assume that the decision boundary separating the classes is a linear function of the input features. In other words, these algorithms try to find a linear equation (a straight line in two dimensions, a plane in three dimensions, or a hyperplane in higher dimensions) that best separates the data points of different classes. Linear classification algorithms include techniques like logistic regression and support vector machines (SVMs) with linear kernels. These algorithms work well when the relationship between the input features and the classes is approximately linear [13].
- **Nonlinear classification:** On the other hand, refers to the decision boundary that separates classes in a classification problem. In linear classification, it is assumed that the decision boundary is a linear function of the input features. This means that the boundary that separates classes is a straight line (in two dimensions), a plane (in three dimensions), or a hyperplane (in higher dimensions). Linear classifiers like logistic regression and linear support vector machines work well when the relationship between input features and classes are approximately linear. In nonlinear classification, the decision boundary is not a straight line, plane, or hyperplane. Instead, it can have curves, twists, or other complex shapes [13].

The steps that can be applied to create a classification model are as follows:

1. **Data collection and preprocessing:** Collect the dataset and perform data preprocessing tasks, such as data cleaning, handling missing values, and transforming variables if necessary. This step ensures that the dataset is in a suitable format for the classification model and that the data are harmonized.
2. **Model initialization:** Choose an appropriate classification algorithm or model for the task at hand. Select from options such as logistic regression, decision trees, random forests, or support vector machines based on the problem and data characteristics.
3. **Cross-validation and dataset separation:** Split the dataset into training and testing subsets using cross-validation techniques. This helps evaluate the model's performance by training on a portion of the data and testing on unseen data, allowing the detection of issues such as overfitting or underfitting.
4. **Training the model:** Feed the training data into the classifier model. The model learns from the labeled training data and adjusts its internal parameters to discover the best decision boundaries or rules for classification. Iteratively update the model based on the training data until satisfactory performance is achieved.
5. **Evaluating the model performance:** Once the model is trained, evaluate it as a newly created classifier on the evaluation dataset. Apply the learned decision boundaries or rules to classify attributes with unknown labels into predefined classes, providing insights and aiding decision making.

Below, Figure 1 serves as an informative illustration depicting the crucial phases in the development of a classification model. This flowchart offers a comprehensive overview of the essential steps required to establish a classifier with the capability to address a wide range of classification tasks.

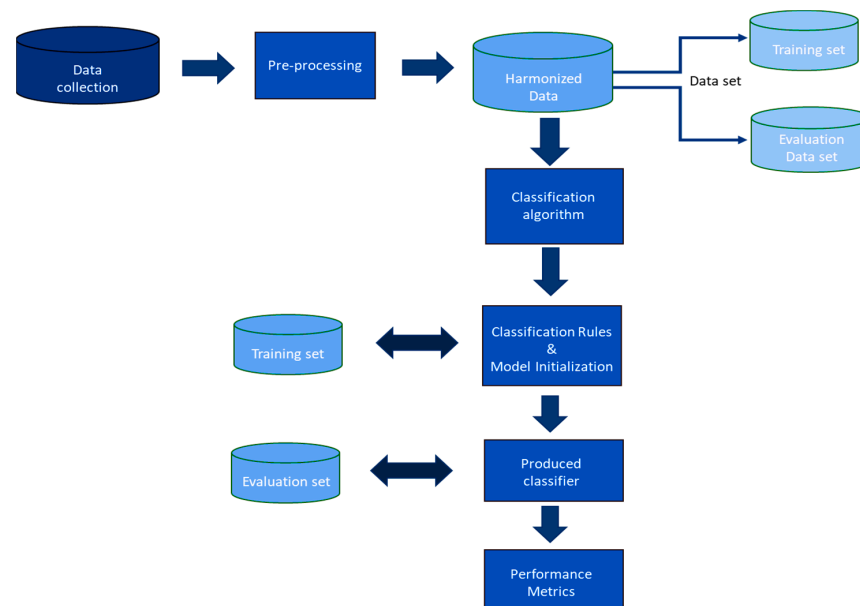


Figure 1. A flowchart illustrating the key steps for creating a classification model.

By following these numbered steps, a classification model can be developed and utilized to classify new observations based on their features, enabling various applications in fields such as healthcare, finance, and customer behavior analysis [17].

Beneath, Table 1, provides a comprehensive overview of various linear classification techniques. These algorithms assume that the decision boundary separating different classes is a linear function of the input features.

Using the table above, we have now linked all the aforementioned water management methodologies, mapping them to specific linear classification approaches, and provided the relevant applications along with supported publication references for verification. We depict this linkage in the following Table 2.

Table 1. Linear classification algorithms.

Algorithm	Ref.	Description
Logistic regression	[33]	Logistic regression models the probability of a binary outcome by fitting a linear function to the input features and applying a logistic (sigmoid) function to obtain the predicted class probabilities. It is widely used for binary classification tasks.
Support vector machine (SVM)	[34]	SVM is a powerful linear classification algorithm that aims to find an optimal hyperplane that separates the input data into different classes. It maximizes the margin between the hyperplane and the nearest data points from each class. SVM can also handle nonlinear data by using kernel functions to map the data into a higher-dimensional space.
Perceptron	[35]	The perceptron algorithm is a fundamental linear classification algorithm. It is a single-layer neural network that learns to classify input data into two classes by adjusting their weights based on misclassification errors.
Ridge classifier	[36]	Ridge classifier is a linear classification algorithm that employs ridge regression to address the issue of multicollinearity in the input features. It introduces a regularization term to the logistic regression cost function, but applies L2 regularization, which helps stabilize the model and reduce the impact of correlated features.
Lasso classifier	[37]	The lasso classifier is similar to logistic regression but applies L1 regularization, resulting in sparse feature selection. It can be useful for identifying the most relevant features when dealing with high-dimensional datasets and reducing model complexity.

Table 1. *Cont.*

Algorithm	Ref.	Description
Elastic net classifier	[38]	The elastic net classifier combines both L1 (lasso) and L2 (ridge) regularization terms to overcome the limitations of each. It strikes a balance between feature selection and feature grouping, making it effective in scenarios with correlated features and when there are more predictors than observations.
Least squares classifier	[39]	The least squares classifier, also known as linear regression for classification, fits a linear function to the input features using the least squares method. It assigns class labels based on the threshold of the predicted continuous values. It can be used for both binary and multiclass classification.
Stochastic gradient descent (SGD) classifier	[40]	The SGD classifier optimizes the model parameters using stochastic gradient descent. It updates the weights with a small subset of training samples (minibatches) at each iteration, making it efficient for large-scale datasets. It is widely used for linear classification problems and can be extended to handle nonlinear data using kernel tricks.
Naïve Bayes classifier	[41]	Naïve Bayes is a probabilistic linear classification algorithm based on Bayes' theorem. It assumes that the features are conditionally independent given the class label. Naïve Bayes calculates the probability of each class and predicts the class with the highest probability. When using linear kernels, naïve Bayes can be considered a linear classifier.
Linear discriminant analysis (LDA)	[42]	LDA is a linear classification algorithm that models the distribution of each class by assuming a Gaussian distribution. It projects the input data onto a lower-dimensional space while maximizing the class separability. The algorithm then assigns the class based on the projected values.
Passive aggressive classifier	[43]	The passive aggressive algorithm is a linear classification algorithm that is especially useful for online learning scenarios. It updates the weights based on misclassification errors, but in a more "passive" or "aggressive" manner depending on the confidence of the prediction. This algorithm is suitable for situations where the data distribution might change over time.
Quadratic discriminant analysis (QDA)	[44]	QDA is a variant of LDA that allows for quadratic decision boundaries. While it involves quadratic terms, it can be considered a linear classifier if the feature space is transformed to include those quadratic terms. QDA models the distribution of each class using quadratic terms and assigns class labels based on the calculated probabilities.

Table 2. Linear classification algorithms for water resources management.

Category	Algorithm	Description	Applications	Ref.
Hydrological modeling	Logistic regression	Statistical modeling for hydrological data.	Predicting flood occurrence based on rainfall data.	[45]
	Support vector machine	SVM-based modeling for hydrology.	Forecasting drought severity using climate data.	[46]
	Naïve Bayes classifier	Probabilistic classification for water quality.	Identifying waterborne contaminants in drinking water.	[47]
Water quality analysis	Ridge classifier	Regularized classification for water quality.	Detecting sources of pollution in rivers and lakes.	[48]
	Lasso classifier	Lasso-based classification for water resources.	Classifying land use for urban water management.	[49]
	Elastic net classifier	Elastic net regularization for water data.	Monitoring and classifying water sources for quality.	[50]
Streamflow forecasting	Least squares classifier	Linear regression for streamflow prediction.	Forecasting river discharge for flood risk assessment.	[51]
	Stochastic gradient descent (SGD) classifier	Gradient-based modeling for streamflow.	Real-time streamflow forecasting for water resource planning.	[52]
Data-driven analysis	Linear discriminant analysis (LDA)	Dimensionality reduction for water data.	Feature extraction for water quality classification.	[53]

Table 2. *Cont.*

Category	Algorithm	Description	Applications	Ref.
Water resources classification	Passive aggressive classifier	Online learning for water resource classification.	Land use classification for watershed management.	[54]
	Quadratic discriminant analysis (QDA)	Nonlinear classification for water data.	Ecosystem classification in aquatic environments.	[55]
	Perceptron	Simple binary classification algorithm.	Initial water quality classification in field surveys.	[56]

Table 3 provides an understandable overview of various nonlinear classification techniques. These methods are specifically designed for scenarios where the decision boundary separating different classes is not a linear function of the input features.

Table 3. Nonlinear classification algorithms.

Algorithm	Ref.	Description
Support vector machine (SVM)	[57]	SVM is a powerful algorithm that can perform both linear and nonlinear classification by transforming the data into a higher-dimensional feature space. It finds the optimal hyperplane that maximizes the margin between different classes.
Decision trees	[58]	Decision trees partition the feature space into smaller regions based on different attribute values. They can capture nonlinear relationships by splitting the data based on various conditions at each internal node. The data are separated into specific parameters and located in nodes, while decisions are contained in leaves. The use of decision trees helps us better approximate and interpret categorical and quantitative values, as well as address issues like filling in missing values in attributes with the most likely value.
Random forest	[9,59]	Random forest is an ensemble method that combines multiple decision trees. It creates a diverse set of trees by using random subsets of the features and then aggregates their predictions to make the final classification. The goal of this method is to reduce the number of variables required to make a prediction, alleviate the data collection burden, accurately evaluate the prediction error rate, and improve efficiency in terms of the number of variables, computation times, and the area under the receiver operating curve.
Gradient boosting	[60]	Gradient boosting is another ensemble method that builds a sequence of weak learners (typically decision trees) in a stage-wise manner. Each subsequent learner focuses on correcting the mistakes made by the previous ones, resulting in a powerful nonlinear classifier.
K-nearest neighbors (KNN)	[61]	KNN classifies new instances based on their proximity to labeled instances in the training data. It can handle nonlinear classification by considering the class labels of the k-nearest neighbors. The KNN algorithm calculates the probability that the test data belong to the classes of the “K” training data, and the class with the highest probability will be selected.
Neural networks	[62]	Neural networks consist of interconnected nodes (neurons) organized in layers. By using nonlinear activation functions and multiple hidden layers, neural networks can capture complex nonlinear relationships between the input features and the target variable.
Gaussian naïve Bayes	[63]	Gaussian naïve Bayes assumes that features are normally distributed and calculates the posterior probability of each class using Bayes’ theorem. Although it assumes feature independence, it can still capture nonlinear decision boundaries in the data.
Kernel methods (e.g., kernel SVM)	[64]	Kernel methods use a nonlinear mapping of the input space to a higher-dimensional feature space. By using a kernel function, they can implicitly compute the dot products in the higher-dimensional space, enabling nonlinear classification.
Bayesian networks	[65]	Bayesian networks model the probabilistic relationships among variables using directed acyclic graphs. They can capture nonlinear dependencies between variables and are particularly useful when dealing with uncertain data.

In Table 4, we establish connections between different water management methods and their specific nonlinear classifications, along with practical applications and supporting references for verification.

Table 4. Nonlinear classification algorithms for water resources management.

Category	Algorithm	Description	Applications	Ref.
Hydrological modeling	Support vector machines (SVMs)	SVM-based modeling for classification.	Flood risk assessment based on historical data.	[66]
	Decision trees	Tree-based models for classification.	Predicting river flow patterns in watersheds.	[67]
	Random forest	Ensemble of decision trees for improved accuracy.	Forest cover classification for water conservation.	[68]
	Gradient boosting	Ensemble method for boosted decision trees.	Estimating groundwater contamination sources.	[69]
Water quality analysis	K-nearest neighbor (KNN)	Classify data based on neighboring points.	Water quality monitoring using sensor networks.	[70]
	Neural networks	Deep learning models with multiple layers.	River pollution detection from satellite imagery.	[71]
	Gaussian naïve Bayes	Probabilistic classifier based on Bayes' theorem.	Forecasting of lake water quality and algal bloom prediction in reservoirs.	[72]
	Kernel methods (e.g., kernel SVM)	Nonlinear classification with kernel functions.	Soil moisture prediction for agricultural planning.	[73]
Data-driven analysis	Bayesian networks	Probabilistic graphical models for classification.	Hydrological risk assessment in watersheds.	[74]

2.1.2. Regression

Regression belongs to the field of supervised ML and is primarily used for predicting continuous numerical values [75]. It is a statistical method that aims to understand the relationship between independent variables, denoted as X (input variables), and dependent variables, denoted as Y (continuous output). Regression plays a crucial role in developing prediction models within ML. In regression, the model is trained using a set of labeled data known as the training data. The training process involves finding the best-fitting line or curve that represents the relationship between the input variables and the continuous output. Once the model is trained, it can be used to make predictions on new, unlabeled data called the test data [15]. The model utilizes the learned patterns from the training data to estimate the output values for the test data. There are various regression methods available, each suited for different scenarios. However, regression can generally be classified into two main categories: simple linear regression and multiple regression [76].

Simple linear regression involves establishing a linear relationship between a single input variable and the output variable. The goal is to find a straight line that best fits the data points, minimizing the overall error or the vertical distance between the observed and predicted values [76].

Multiple regression involves predicting a dependent variable based on two or more independent variables. It assumes a linear relationship between the variables, meaning that the change in the dependent variable is assumed to be proportional to the change in the independent variables [76].

Nonlinear regression is used when the relationship between the dependent and independent variables is not linear. It models relationships that may follow curves, exponential growth, or other nonlinear patterns [77].

Regression analysis provides valuable insights into the relationships between variables and helps in making predictions or estimating values for new observations.

Downward, Table 5 provides a concise overview of diverse linear regression algorithms. These methods are fundamental tools for modeling linear relationships between variables, making them valuable in numerous statistical and machine learning applications.

Table 5. Linear regression algorithms.

Algorithm	Ref.	Description
Ordinary least squares (OLS)	[78]	OLS is a commonly used linear regression algorithm that minimizes the sum of squared residuals to find the best-fitting line. It assumes a linear relationship between the input variables and the output.
Ridge regression	[79]	Ridge regression is a regularized linear regression algorithm that adds a penalty term to the least squares objective function. It helps reduce the impact of multicollinearity and can prevent overfitting.
Lasso regression	[80]	Lasso regression is a regularized linear regression algorithm that adds a penalty term based on the absolute values of the coefficients. It promotes sparsity by shrinking some coefficients to exactly zero.
Elastic net regression	[81]	Elastic net regression combines L1 (lasso) and L2 (ridge) regularization to address some limitations of both methods. It balances between variable selection and coefficient shrinkage.
Bayesian linear regression	[82]	Bayesian linear regression incorporates prior knowledge about the coefficients and allows for probabilistic inference. It estimates a posterior distribution over the coefficients using Bayes' theorem.
Stepwise regression	[83]	Stepwise regression is an iterative method that automatically selects a subset of input variables by adding or removing them based on statistical criteria. It helps to build a parsimonious model.

In Table 6, we correlate various water management methodologies with distinct linear regression techniques. We also provide applications and publication references for validation.

Table 6. Linear regression algorithms for water resources management.

Category	Algorithm	Description	Applications	Ref.
Regression and water resources management	Ordinary least squares (OLS)	Minimizes the sum of squared differences between observed and predicted values.	River flow forecasting, reservoir management.	[84]
Hydrological modeling and prediction	Ridge regression	Adds L2 regularization to OLS, helps prevent overfitting by adding a penalty for large coefficients.	Groundwater level prediction, water quality modeling.	[85]
Water quality analysis and pollution tracking	Lasso regression	Adds L1 regularization to OLS, encourages sparse coefficient selection by penalizing nonessential features.	Streamflow modeling, feature selection in hydrology.	[86]
Hydrological modeling and data fusion	Elastic net regression	Combines L1 (lasso) and L2 (ridge) regularization to balance feature selection and coefficient shrinkage.	Hydrological modeling, water resource optimization.	[87]
Water resource allocation and management	Bayesian linear regression	Uses Bayesian framework to estimate model parameters and uncertainty in predictions.	Flood risk assessment, climate change impact modeling.	[88]
Environmental data analysis and modeling	Stepwise regression	Iteratively adds or removes predictors to build the best-fitting model.	Water resource allocation, reservoir operation optimization.	[89]

Table 7 provides a concise overview of various nonlinear regression algorithms. Nonlinear regression is a powerful approach for modeling relationships between variables when the underlying patterns are not strictly linear. These algorithms are essential tools in data analysis and machine learning, enabling the modeling of complex, nonlinear associations in various applications.

Table 7. Nonlinear regression algorithms.

Algorithm	Ref.	Description
Polynomial regression	[90]	Fits a polynomial function to the data by including higher-order terms of the input variables. It can capture nonlinear relationships by introducing polynomial features, allowing for more flexible curve fitting.
Support vector regression (SVR)	[91]	Uses support vector machines to perform regression. It aims to find a nonlinear function that best fits the data by mapping the input variables to a higher-dimensional feature space. SVR uses a loss function that allows for a certain tolerance or margin around the predicted values, providing flexibility to capture nonlinear patterns.

Table 7. Cont.

Algorithm	Ref.	Description
Decision tree regression	[92]	Builds a regression model by recursively splitting the data based on the values of the input variables. Each internal node represents a test on a specific feature, and each leaf node represents a predicted value. Decision trees can capture complex nonlinear relationships and are easily interpretable.
Random forest regression	[93]	An ensemble learning method that combines multiple decision trees to perform regression. It constructs a multitude of decision trees and generates predictions by averaging the predictions of individual trees. Random forest regression is capable of handling nonlinear relationships and reducing overfitting.
Gradient boosting regression	[60]	Builds a regression model by iteratively adding weak learners, typically decision trees, to minimize the loss function. It constructs an ensemble of models where each subsequent model focuses on reducing the errors made by the previous models. Gradient boosting regression can effectively capture nonlinear relationships and handle complex datasets.
Neural network regression	[94]	Utilizes artificial neural networks (ANNs) to perform regression. ANNs consist of interconnected nodes (neurons) organized into layers. By learning the weights and biases of these connections, neural networks can model complex nonlinear relationships between input variables and the target variable.
K-nearest neighbor (KNN) regression	[95]	Predicts the target variable based on the average of the values of its k-nearest neighbors in the feature space. KNN regression can capture nonlinear relationships by considering local patterns in the data.
Gaussian process regression	[96]	Uses a Gaussian process to model the relationship between the input variables and the target variable. It can capture complex nonlinear relationships and provides uncertainty estimates for predictions.
Support vector machines (SVMs)	[97]	Originally designed for classification, SVM can be extended to regression tasks. It aims to find a hyperplane that best separates the data points while maximizing the margin. SVM regression can handle nonlinear relationships by using kernel functions.
Bayesian regression	[98]	Combines prior knowledge with observed data to estimate the posterior distribution of the model parameters. Bayesian regression can capture nonlinear relationships by using flexible probabilistic models.

Table 8 links different water management methods with nonlinear regression approaches, along with their practical applications and supporting references.

Table 8. Nonlinear regression algorithms for water resources management.

Category	Algorithm	Description	Applications	Ref.
Regression and water resources management	Polynomial regression	Fits a polynomial equation to the data, allowing for curved relationships between variables.	Time-series forecasting, hydrological modeling.	[99]
Hydrological modeling and prediction	Support vector regression (SVR)	Uses support vector principles to find a hyperplane that best fits the data in a higher-dimensional space.	Groundwater level prediction, water quality modeling.	[100]
Water quality analysis and prediction	Decision tree regression	Uses a tree-like model to represent decisions based on feature values, suitable for nonlinear relationships.	River flow forecasting, water resource optimization.	[101]
Hydrological modeling and risk assessment	Random forest regression	Ensemble of decision trees to improve prediction accuracy and reduce overfitting.	Land use change prediction, flood risk assessment.	[102]
Streamflow forecasting and hydrology	Gradient boosting regression	Builds multiple decision trees sequentially, each correcting the errors of the previous one.	Streamflow modeling, feature selection in hydrology.	[103]
Hydrological data modeling and analysis	Neural network regression	Utilizes artificial neural networks to model complex relationships between inputs and outputs.	Rainfall-runoff modeling, water demand forecasting.	[104]
Water resource allocation and prediction	K-nearest neighbor (KNN) regression	Predicts values based on the average of its k-nearest neighbors in the training dataset.	Water quality prediction, aquifer characterization.	[105]
Environmental data analysis and modeling	Gaussian process regression	Models the relationship between variables as a distribution, allowing for uncertainty quantification.	Climate modeling, uncertainty analysis.	[106]
Water resource management and assessment	Bayesian regression	Uses Bayesian framework to estimate model parameters and uncertainty in predictions.	Flood risk assessment, climate change impact modeling.	[107]

2.2. Unsupervised Learning

Unsupervised learning, also known as observational learning, is a branch of ML that focuses on analyzing and clustering unlabeled datasets. Unlike supervised learning, which relies on labeled data for training, unsupervised learning algorithms work with unannotated data to identify hidden patterns and groupings. This approach enables the algorithms to discover insights and extract meaningful information from the data without human intervention.

The primary goal of unsupervised learning is to discern similarities and differences within the dataset, facilitating tasks such as data segmentation and image recognition [108]. By autonomously exploring the data, unsupervised learning algorithms can uncover underlying structures and relationships that might not be immediately apparent.

There are two main methods commonly used in unsupervised learning: clustering and association.

Clustering algorithms aim to group similar data points together based on their inherent characteristics [109]. These algorithms employ various techniques, such as density-based clustering, hierarchical clustering, or k-means clustering, to identify clusters or groups of clusters within the dataset. By organizing the data into meaningful groups, clustering enables researchers and practitioners to gain insights into the underlying patterns and structures present in the data.

Association algorithms, on the other hand, focus on discovering relationships and associations between different variables in the dataset [110]. These algorithms search for frequent co-occurrence patterns or associations among items, enabling the identification of rules or correlations. Association analysis has applications in various fields, including market basket analysis, recommender systems, and anomaly detection.

Both clustering and association methods provide valuable tools for exploratory data analysis and knowledge discovery. Unsupervised learning algorithms play a crucial role in extracting useful information from unlabeled datasets, enabling researchers and practitioners to uncover hidden insights, generate hypotheses, and make data-driven decisions.

2.2.1. Clustering

Clustering, as an unsupervised learning method, plays a crucial role in organizing unlabeled data into groups of similarity known as clusters. Each cluster represents a collection of data points that exhibit similar characteristics, and these clusters can vary in terms of their similarity or dissimilarity to data points in other clusters [111]. The main objective of clustering is to identify groups of similar objects within a dataset while ensuring that dissimilar objects are separated into different clusters or labeled as noise points [112].

From a statistical analysis perspective, clustering involves examining the underlying structure and patterns present in the data. By leveraging similarity metrics and distance measures, clustering algorithms aim to partition the data in a way that maximizes intracluster similarity and minimizes intercluster dissimilarity. This process enables the identification of natural groupings or clusters within the dataset [113].

The applications of clustering extend across various fields, including ML, data mining, pattern recognition, image analysis, and bioinformatics. In ML, clustering can be employed to group similar instances together, aiding in tasks such as customer segmentation, anomaly detection, and recommendation systems. In data mining, clustering assists in exploratory data analysis, helping researchers discover hidden patterns and structures within large datasets. Pattern recognition leverages clustering to identify similar objects or patterns in images, texts, or signals. Image analysis techniques often utilize clustering to segment images into meaningful regions or objects. In the field of bioinformatics, clustering helps identify groups of genes with similar expression patterns or clusters proteins based on their functional similarities [113].

Clustering algorithms have evolved to encompass various approaches, each with its own strengths and suitability for different types of data. These algorithms consider factors such as data distribution, distance metrics, and cluster representation to effectively

organize the data. The k-means algorithm partitions the data into a predetermined number of clusters based on the centroids, while hierarchical clustering builds a hierarchy of clusters through merging or splitting. Expectation maximization employs probabilistic models to estimate the parameters of the underlying distribution, and density-based clustering focuses on regions of high density in the data space [111,112].

By employing clustering techniques, researchers and practitioners can gain valuable insights into complex datasets, enabling them to make informed decisions, identify patterns, and extract meaningful information. Clustering serves as a fundamental tool for uncovering hidden structures and relationships within unlabeled data, ultimately contributing to advancements in various domains.

Table 9 presents an overview of various clustering algorithms. Clustering is a crucial technique in data analysis and machine learning that groups similar data points together based on certain criteria. These algorithms play a pivotal role in uncovering patterns and structures within data, making them essential for tasks such as customer profiling, pattern recognition, and anomaly detection.

Table 10 provides a concise summary of common error functions used in clustering. Error functions are essential for evaluating the quality and performance of clustering algorithms. These functions help quantify the dissimilarity between data points and cluster centroids, aiding in the assessment and optimization of clustering results.

In Table 11, we establish connections between water management methodologies and specific nonlinear regression techniques, highlighting applications and references for verification.

Table 9. Clustering algorithms.

Algorithm	Ref.	Description
K-means	[114]	K-means is an iterative algorithm that divides data into k clusters. It aims to minimize the sum of squared distances within each cluster. Initially, k centroid points are randomly assigned, and each data point is assigned to the nearest centroid. The centroids are updated iteratively by computing the mean of the points within each cluster until convergence is achieved.
DBSCAN	[115]	DBSCAN is a density-based clustering algorithm that groups data points based on their density. It defines clusters as dense regions separated by areas of lower density. The algorithm starts with an arbitrary point and expands the cluster by adding nearby points that have a sufficient number of neighbors within a specified distance. Outliers are considered as points with low density and are not assigned to any cluster.
Hierarchical clustering	[116]	Hierarchical clustering builds a tree-like structure of clusters by iteratively merging or splitting clusters based on similarity. It can be agglomerative, starting with individual data points as separate clusters and merging the most similar ones, or divisive, starting with a single cluster and recursively splitting it into smaller clusters. The result is a dendrogram that provides insights into the hierarchical structure of the data.
Gaussian mixture models (GMMs)	[117]	GMM assumes that the data are generated from a mixture of Gaussian distributions. It models each cluster as a Gaussian distribution with its own mean and covariance matrix. The algorithm estimates the parameters of the Gaussian components using the expectation maximization (EM) algorithm, which maximizes the likelihood of the observed data. GMM provides probabilistic cluster assignments, allowing soft assignments where data points can belong to multiple clusters with varying probabilities.
Mean shift	[118]	Mean shift is an iterative algorithm that aims to find the modes or peaks of the data distribution. It starts with an initial set of points and iteratively shifts them towards the direction of the highest density, which is determined by a kernel density estimation. The algorithm continues until convergence, resulting in clusters centered around the modes of the data distribution.
Spectral clustering	[119]	Spectral clustering transforms the data into a lower-dimensional space using eigenvectors of a similarity matrix and then applies traditional clustering techniques. It considers the pairwise similarity between data points and constructs a similarity matrix. The eigenvectors corresponding to the largest eigenvalues are used to embed the data into a lower-dimensional space, where clustering algorithms like k-means or Gaussian mixture models can be applied. Spectral clustering can handle nonlinearly separable data and is particularly effective for graph-based clustering.
OPTICS	[120]	OPTICS (ordering points to identify the clustering structure) is a density-based clustering algorithm similar to DBSCAN. It creates a reachability plot that represents the ordering of data points based on their density reachability. It captures both dense regions and density-based hierarchical relationships in the data. OPTICS is particularly useful for analyzing the varying density of clusters and identifying clusters of different sizes and shapes.
Agglomerative clustering	[121]	Agglomerative clustering is a hierarchical clustering algorithm that starts with each data point as a separate cluster and iteratively merges the most similar clusters until a stopping criterion is met. It can be based on various distance metrics and linkage criteria such as single linkage, complete linkage, or average linkage. The result is a dendrogram that shows the hierarchical structure of the data.
Density-based clustering	[122]	Density-based clustering algorithms identify clusters as areas of high data density separated by regions of low density. These algorithms, such as DBSCAN and OPTICS, do not require specifying the number of clusters in advance and can handle datasets with varying densities and irregular shapes. They are robust to noise and capable of identifying outliers.

Table 10. Common error functions in clustering.

Metric.	Ref.	Description
Calinski–Harabasz	[123]	The CH index measures the quality of a clustering algorithm by evaluating the distance between cluster centroids and the global centroid (numerator), and the distances between centroids within each cluster (denominator). A higher CH index indicates a valid optimal partition with well-separated clusters.
Chou–Su–Lai	[124]	The CS index assesses the quality of a clustering partition by calculating the sum of average maximum distances within each cluster (numerator) and the sum of minimum distances between clusters (denominator). The clustering partition with the smallest CS index is considered valid and optimal.
Dunn’s index	[125]	The DI index evaluates the quality of a partition by measuring the minimum between-cluster distance (numerator) and the maximum within-cluster distance (denominator). An optimally valid partition is indicated by the largest DI index.
Davies–Bouldin’s index	[126]	The DB index measures the quality of a clustering partition, with the optimal partition identified by the smallest DB index value.
Davies–Bouldin’s index	[127]	The DB index identifies a valid and optimal partition, similar to the original DB index, with the smallest DB value indicating the optimal partition.
Silhouette coefficient	[128]	An optimal and valid partition is indicated by the largest SC (silhouette coefficient) value.
Hybrid validity index	[129]	SCD (cluster validity index) encompasses three robust measures of cluster validity: silhouette coefficient (SC), connectivity and separation (CS), and Davies–Bouldin (DB) index.

Table 11. Clustering algorithms for water resources management.

Category	Algorithm	Description	Applications	Ref.
Water resources management and analysis	K-means	Divides water quality data into clusters based on similarity, aiding in pollution source identification.	Water quality analysis, source tracking.	[130]
Water resources management and monitoring	DBSCAN	Identifies spatial clusters of monitoring stations for efficient water quality network design.	Sensor network optimization, anomaly detection.	[131]
Hydrological modeling and watershed planning	Hierarchical clustering	Groups similar hydrological stations for the purpose of watershed delineation and land use classification.	Watershed management, land use planning.	[132]
Hydrological data analysis and modeling	Gaussian mixture models (GMMs)	Models complex hydrological data patterns to identify different flow regimes in river systems.	Hydrological data modeling, flow regime analysis.	[133]
Rainfall pattern analysis and forecasting	Mean shift	Detects peaks in rainfall patterns to identify areas with similar precipitation characteristics.	Rainfall pattern analysis, flood forecasting.	[134]
Remote sensing and water quality monitoring	Spectral clustering	Clusters remote sensing images of water bodies to monitor changes in water quality and quantity.	Remote sensing in water resources, image analysis.	[135]
Environmental impact assessment and monitoring	OPTICS	Identifies spatial clusters of water quality anomalies for environmental hotspot detection.	Water quality monitoring, anomaly identification.	[136]
Hydrological network design and data collection	Agglomerative clustering	Clusters hydrological monitoring stations to optimize network design for efficient data collection.	Hydrological network design, data collection.	[137]
Anomaly detection and environmental assessment	Density-based clustering	Detects anomalies in water quality data, such as pollutant spikes, for environmental impact assessment.	Anomaly detection in water quality data.	[138]

2.2.2. Association Rules

Association rules mining is a powerful and popular unsupervised data mining technique that aims to uncover meaningful associations, relationships, and dependencies within vast collections of data items. This method operates on data that are typically organized in the form of transactions, which can be generated through an external process or extracted from relational databases and data warehouses [139]. By examining these transactions, association rules mining endeavors to discover valuable patterns and connections that may be hidden within the data, providing valuable insights and facilitating decision-making processes in various domains. This approach is particularly useful in tasks such as market basket analysis, customer segmentation, recommendation systems, and fraud detection, where identifying significant associations between different items can lead to enhanced understanding, improved efficiency, and better decision outcomes [140]. Table 12 provides a concise summary of association rules algorithms. These algorithms are fundamental tools

in the realm of data mining and analytics, empowering the revelation of captivating and occasionally surprising connections within vast datasets.

Table 13, connects various water management methods with association rules approaches, practical applications, and supporting references for validation.

Table 12. Association rules algorithms.

Algorithm	Ref.	Description
Apriori	[141]	Apriori is a classic algorithm for mining frequent itemsets and generating association rules. It uses a breadth-first search approach to discover itemsets and prune infrequent ones based on minimum support.
FP-Growth	[142]	FP-Growth is an algorithm that efficiently discovers frequent itemsets by using a prefix tree (FP-tree) data structure. It avoids candidate generation and employs a divide-and-conquer strategy for mining.
Eclat	[143]	Eclat (equivalence class transformation) is an algorithm for mining frequent itemsets based on vertical data format. It uses a depth-first search strategy to explore the itemset lattice and identify frequent itemsets.
CAR-SPAN	[144]	CAR-SPAN (closed and approximate repeated sequential pattern mining) is an algorithm that discovers closed and approximate frequent sequential patterns. It adopts a two-phase approach involving pattern growth and pruning.
FPMMax	[145]	FPMMax is an algorithm that extends FP-Growth to mine maximal frequent itemsets. It efficiently discovers itemsets that are not a subset of any other frequent itemsets, reducing redundancy in the results.
RuleGrowth	[146]	RuleGrowth is an algorithm that integrates pattern growth and rule generation. It discovers frequent itemsets using a compact pattern tree and generates high-quality association rules based on interestingness measures.
R-Mine	[147]	R-Mine is an algorithm that mines rules from relational databases. It uses a lattice structure to represent itemsets and employs an efficient method for computing the support of rules.
Tertius	[148]	Tertius is an algorithm that focuses on mining association rules with time constraints in transactional databases. It incorporates temporal information to capture time-dependent associations in the data.

Table 13. Association rules algorithms for water resources management.

Category	Algorithm	Description	Applications	Ref.
Data mining and water resources management	Apriori	Discovers frequent itemsets in water quality data for association rule mining.	Pattern discovery in water quality data, anomaly detection.	[149]
Data mining and hydrological analysis	FP-Growth	Efficiently mines frequent patterns in hydrological time series data.	Hydrological pattern discovery, streamflow analysis.	[150]
Water quality analysis and pattern mining	Eclat	Identifies frequent itemsets in water quality datasets, aiding in pollution source identification.	Water quality assessment, pollution source tracking.	[151]
Data mining and water quality monitoring	CAR-SPAN	Discovers closed frequent patterns in sensor data to monitor water quality changes.	Sensor network data analysis, water quality monitoring.	[152]
Hydrological pattern recognition	FPMMax	Extends FP-Growth for maximal frequent pattern mining in hydrological datasets.	Hydrological pattern recognition, rainfall analysis.	[153]
Data mining and environmental assessment	RuleGrowth	Mines association rules to identify relationships between environmental variables.	Environmental impact assessment, ecological modeling.	[154]
Hydrological data analysis and pattern mining	R-Mine	Discovers recurring patterns in hydrological time series data.	Hydrological forecasting, drought prediction.	[155]
Data mining and water resource allocation	Tertius	Supports decision making in water allocation by mining patterns in water usage data.	Water resource allocation optimization, demand management.	[156]

2.3. Semisupervised Learning

Semisupervised learning (SSL) is a powerful technique in ML that combines the benefits of both supervised and unsupervised learning approaches. While supervised learning requires large amounts of labeled training data to classify new data accurately, which can be time-consuming and costly to obtain, unsupervised learning lacks the ability to properly identify and cluster unknown data accurately. To address these limitations, SSL leverages a combination of labeled and unlabeled data during the training process. It starts with a small set of labeled patterns, where each pattern is associated with a known label. The model then utilizes these labeled patterns to learn the underlying patterns and relationships within the data. This process is similar to traditional supervised learning. However, what makes SSL unique is that it also takes advantage of the larger set of unlabeled patterns. These unlabeled patterns do not have corresponding labels but contain valuable information about the data's distribution and structure. By incorporating this unlabeled data, the model can gain a more comprehensive understanding of the dataset and generalize better to unseen data. It is divided into two types: (i) semisupervised classification and (ii) semisupervised clustering [157].

2.3.1. Semisupervised Classification

Semisupervised classification is an ML approach that combines labeled and unlabeled data to enhance model performance. By leveraging the additional information present in the unlabeled data, it helps improve the accuracy and generalization capabilities of the model.

One of the key advantages of semisupervised classification is its ability to reduce the reliance on large amounts of labeled data. Labeled data can be scarce, expensive, or time-consuming to obtain, while unlabeled data are often more abundant and easily accessible. By incorporating unlabeled data into the learning process, the model can make use of the additional information to learn more robust and representative patterns from the data.

Semisupervised classification techniques typically involve utilizing the structure or distribution of the unlabeled data. This can be achieved through methods such as clustering, where the unlabeled data are grouped based on similarities, or by leveraging density estimation techniques to identify regions of high density within the data. These approaches help the model capture the underlying structure of the data, resulting in improved classification performance.

By combining labeled and unlabeled data, semisupervised classification strikes a balance between the benefits of supervised and unsupervised learning. It allows the model to benefit from the guidance provided by labeled data while also leveraging the information embedded in the unlabeled data. This approach is particularly valuable in situations where acquiring labeled data is challenging, expensive, or time-consuming, making it a powerful tool in various real-world applications [157]. Table 14 offers a compact overview of semisupervised classification algorithms. These algorithms are essential tools in machine learning, bridging the gap between labeled and unlabeled data to enhance the accuracy of classification tasks.

Table 15 illustrates the relationships between different water management methods and semisupervised classification techniques, including applications and verification references.

2.3.2. Semisupervised Clustering

Semisupervised clustering is a powerful approach that combines labeled and unlabeled data to enhance clustering accuracy and interpretability. By incorporating labeled information, this technique guides the clustering algorithm to form more meaningful and accurate clusters. Labeled data provide explicit class labels, acting as a valuable anchor in the clustering process. Simultaneously, unlabeled data capture the underlying structure and patterns in the dataset, allowing for noise reduction and improved clustering outcomes.

Table 14. Semisupervised classification algorithms.

Algorithm	Ref.	Description
Self-training	[158]	In self-training, a model is initially trained on the labeled data and then used to make predictions on the unlabeled data. The confident predictions are added to the labeled set, and the process is iterated to improve the model's performance.
Co-training	[159]	Co-training involves training multiple models on different subsets of features or data and then using their predictions to label the unlabeled data. The models iteratively update each other by adding the confident predictions, enhancing classification accuracy.
Multiview learning	[160]	Multiview learning utilizes multiple views or perspectives of the data to improve classification performance. Each view provides different information and combining them leads to a more comprehensive understanding of the underlying patterns and relationships.
Generative models	[161]	Generative models, such as Gaussian mixture models (GMM) or variational autoencoders (VAE), learn the underlying data distribution and generate synthetic samples. These models can be used to generate additional labeled data for training the classification model.
Graph-based methods	[162]	Graph-based methods construct a graph representation of the data, where nodes represent instances and edges capture relationships. Techniques like label propagation or graph-based regularization propagate labels through the graph to classify unlabeled instances.
Transductive support vector machines (TSVMs)	[163]	TSVM treats the labeled and unlabeled data as separate sets and aims to find a decision boundary that separates the labeled instances while considering the unlabeled instances as potential support vectors. It leverages the information in both labeled and unlabeled data for classification.

Table 15. Semisupervised classification algorithms for water resources management.

Category	Algorithm	Description	Applications	Ref.
Machine learning and water resources management	Self-training	Utilizes unlabeled water quality data to improve water quality prediction models.	Water quality prediction, sensor data enhancement.	[164]
Machine learning and hydrological analysis	Co-training	Leverages data from multiple hydrological sensors to enhance streamflow forecasting accuracy.	Hydrological modeling, streamflow prediction.	[165]
Data integration and water quality monitoring	Multiview learning	Combines diverse water quality data sources (e.g., remote sensing and in situ measurements) for more comprehensive assessments.	Water quality assessment, pollution source tracking.	[166]
Machine learning and environmental assessment	Generative models	Generates synthetic environmental data for simulating scenarios in impact assessments.	Environmental impact assessment, scenario modeling.	[167]
Graph-based methods and hydrological analysis	Graph-based methods	Utilizes graph-based representations to model hydrological networks and optimize water resource allocation.	Hydrological network analysis, water allocation optimization.	[168]
Machine learning and environmental monitoring	Transductive support vector machines (TSVMs)	Labels data points based on their relationships with labeled instances, aiding in anomaly detection.	Environmental anomaly detection, sensor data analysis.	[169]

Various techniques, such as constrained clustering and co-training, are employed to effectively integrate labeled and unlabeled data. Constrained clustering leverages the constraints derived from labeled data to guide the clustering process. Co-training utilizes multiple models trained on different subsets of features or data, leveraging their predictions to label the unlabeled instances.

By leveraging both labeled and unlabeled data, semisupervised clustering offers several benefits. It enhances the accuracy and interpretability of clustering results, providing a more comprehensive understanding of the underlying data structure. This facilitates insightful decision making and enables researchers and practitioners to gain valuable insights from their data. Overall, semisupervised clustering is a valuable technique for exploring complex datasets and extracting meaningful patterns [157]. Table 16 offers a brief overview of semi-supervised clustering algorithms. These algorithms are fundamental in the field of clustering, helping to improve clustering accuracy in scenarios involving partially labeled data.

Table 16. Semisupervised clustering algorithms.

Algorithm	Ref.	Description
Co-training clustering	[170]	Co-training clustering utilizes multiple clustering algorithms trained on different subsets of features or data. The algorithms iteratively update each other by assigning labels to the unlabeled data points. By leveraging the agreement between the algorithms, it enhances clustering accuracy and mitigates the impact of noise and outliers.
Self-training clustering	[171]	Self-training clustering initially trains a clustering algorithm on the labeled data and then uses it to cluster the unlabeled data. The most confident cluster assignments are added to the labeled data, and the process is iterated. This approach improves the clustering performance by progressively incorporating the unlabeled data into the training process.
Constrained clustering	[172]	Constrained clustering integrates prior knowledge in the form of constraints into the clustering process. These constraints can be pairwise must-link and cannot-link constraints or other forms of side information. By incorporating the constraints, the algorithm guides the clustering to respect the specified relationships, resulting in more accurate and meaningful clustering outcomes.
Semisupervised expectation maximization (semi-EM)	[173]	Semi-EM is an adaptation of the expectation maximization (EM) algorithm for semisupervised clustering. It incorporates both labeled and unlabeled data in the estimation of cluster parameters. The algorithm iteratively assigns data points to clusters and updates the parameters based on the expectations and maximization steps. Semi-EM improves clustering results by leveraging the information in both labeled and unlabeled data.
Co-EM clustering	[174]	Co-EM clustering is an extension of the EM algorithm for semisupervised clustering. It simultaneously estimates cluster parameters and assigns labels to the unlabeled data points. The algorithm iteratively updates the cluster parameters and refines the labels by incorporating information from both labeled and unlabeled data, improving the clustering accuracy.

Table 17 presents correlations between water management methodologies and semisupervised clustering methods, along with practical applications and references for validation.

Table 17. Semisupervised clustering algorithms for water resources management.

Category	Algorithm	Description	Applications	Ref.
Machine learning and water resources management	Co-training	Enhances water quality prediction models by leveraging data from multiple sources, such as remote sensing and in situ measurements.	Water quality prediction, data fusion from diverse sources.	[175]
Data mining and water quality assessment	Clustering	Clusters water quality data to identify patterns and anomalies for improved monitoring and assessment.	Water quality analysis, anomaly detection in sensor data.	[176]
Machine learning and environmental monitoring	Self-training clustering	Utilizes unlabeled water quality data to improve clustering algorithms for water quality assessment.	Water quality clustering, unsupervised anomaly detection.	[177]
Data integration and environmental assessment	Constrained clustering	Applies constraints to clustering algorithms to account for domain knowledge in water quality analysis.	Water quality clustering with domain-specific constraints.	[178]
Semisupervised learning and environmental data	Semisupervised	Combines labeled and unlabeled environmental data to improve water quality modeling and assessment.	Water quality prediction, leveraging partial labels.	[179]
Statistical modeling and environmental data	Expectation maximization (semi-EM)	Uses the expectation maximization algorithm to estimate parameters in semisupervised water quality models.	Parameter estimation in semi-supervised models.	[180]
Machine learning and environmental data	Co-EM clustering	Integrates expectation maximization and clustering for semisupervised water quality analysis.	Semisupervised clustering in water quality assessment.	[181]

2.4. Reinforcement Learning

Reinforcement learning (RL) is an essential learning method that differs from supervised and unsupervised learning [182]. Unlike other learning approaches, RL focuses on training an agent to maximize its performance by rewarding desirable behaviors and penalizing undesirable ones. The primary objective of RL is to enable machines to surpass known methods and excel in complex decision-making tasks.

In RL, an agent interacts with its environment, perceiving and interpreting its state, taking actions, and receiving feedback in the form of rewards or penalties [183]. Through repeated interactions and learning from trial and error, the agent improves its decision-making abilities and optimizes its behavior to achieve the highest cumulative reward over time.

The scope of RL extends beyond traditional ML domains. It explores how both physical and artificial systems can learn to predict the consequences of their actions and optimize their behavior in dynamic environments [184]. RL finds applications in diverse fields such as ethology, economics, psychology, and control theory. It enables researchers to understand and simulate how organisms and systems adapt, learn, and make decisions based on the outcomes of their actions. By leveraging the principles of RL, researchers aim to develop intelligent systems that can autonomously learn and improve their performance in complex and uncertain environments. RL provides a framework for understanding and modeling the decision-making process, enabling machines to make informed choices and achieve superior performance in a wide range of applications. Table 18 provides an overview of reinforcement learning algorithms. These algorithms are central in the field of machine learning, as they are designed for training agents to make sequential decisions in dynamic environments.

Table 19 shows connections between water management techniques and reinforcement methods, with practical applications and references for verification.

Table 18. Reinforcement algorithms.

Algorithm	Ref.	Description
Q-learning	[185]	Q-learning is a model-free reinforcement learning algorithm that learns an action-value function, known as the Q-function. It iteratively updates the Q-values based on the rewards received and estimates the optimal policy for an agent to maximize its cumulative reward over time.
Deep Q-network (DQN)	[186]	DQN is an extension of Q-learning that utilizes deep neural networks to approximate the Q-values. It overcomes the limitations of traditional Q-learning by enabling the agent to handle high-dimensional state spaces. DQN incorporates experience replay and target networks to stabilize and improve learning performance.
Policy gradient methods	[187]	Policy gradient methods directly learn a parameterized policy that determines the agent's actions based on the observed state. These methods use gradient ascent to iteratively update the policy parameters, aiming to maximize the expected cumulative reward. Common variants include REINFORCE, proximal policy optimization (PPO), and trust region policy optimization (TRPO).
Actor–critic methods	[188]	Actor–critic methods combine policy gradient and value function estimation. The actor learns the policy, while the critic estimates the value function to evaluate the policy's performance. This approach provides a balance between exploring new actions and exploiting the current policy, enhancing the stability and efficiency of learning.
Proximal policy optimization (PPO)	[189]	PPO is a policy optimization algorithm that employs a surrogate objective function to update the policy parameters. It ensures that policy updates remain within a specified range, preventing drastic policy changes. PPO is known for its sample efficiency and stable learning performance, making it a popular choice for continuous control tasks.
Deep deterministic policy gradient (DDPG)	[190]	DDPG is an off-policy actor–critic algorithm that is well suited for continuous action spaces. It uses a deterministic policy to learn the optimal policy, and a deep neural network is employed to approximate both the actor and critic functions. DDPG combines Q-learning and policy gradient methods, enabling stable learning in continuous action domains.
Monte Carlo methods	[191]	Monte Carlo methods estimate the value of states or state–action pairs by averaging the observed returns from sampled trajectories. These methods do not rely on a model of the environment and learn directly from episodes of interaction. They are suitable for episodic tasks where the complete trajectory is available.
Temporal difference (TD) learning	[192]	TD learning combines ideas from both Monte Carlo methods and dynamic programming. It updates value estimates based on bootstrapping, using estimates from subsequent time steps. TD algorithms, such as SARSA and Q-lambda, enable learning during ongoing interactions without requiring complete episodes of experience.
Asynchronous advantage actor–critic (A3C)	[193]	A3C is an actor–critic algorithm that uses multiple agents operating in parallel to learn a policy and value function. Each agent interacts with a separate copy of the environment, and their experiences are asynchronously combined to update the shared network parameters. A3C is known for its scalability and efficient use of computational resources.

Table 18. Cont.

Algorithm	Ref.	Description
Proximal value optimization (PPO)	[194]	PPO is a policy optimization algorithm that focuses on updating the policy within a trust region. It leverages a clipped surrogate objective function to ensure conservative policy updates. PPO offers a balance between sample efficiency and stable learning, making it suitable for a wide range of reinforcement learning tasks.
Soft actor–critic (SAC)	[195]	SAC is an off-policy actor–critic algorithm that incorporates the concept of entropy regularization. It maximizes the expected cumulative reward while also maximizing the entropy of the policy distribution, promoting exploration and robustness. SAC is particularly effective in continuous action spaces and has been successful in various domains, including robotics and control tasks.
Twin delayed deep deterministic policy gradient (TD3)	[196]	TD3 is an off-policy actor–critic algorithm that builds upon DDPG. It addresses overestimation bias and enhances stability by introducing twin critics and delayed policy updates. TD3 has shown improved sample efficiency and robustness in continuous control tasks with large action spaces.

Table 19. Reinforcement algorithms for water resources management.

Category	Algorithm	Description	Applications	Ref.
Reinforcement learning and water resources management	Q-learning	Learns optimal control policies for water resource management through exploration and exploitation.	Optimal water resource allocation, reservoir management.	[197]
Machine learning and hydrological modeling	Deep Q-network (DQN)	Utilizes deep neural networks to approximate Q-values in hydrological decision-making problems.	Flood control, reservoir operation, hydrological modeling.	[198]
Reinforcement learning and environmental management	Policy gradient methods	Directly optimizes the policy of water resource management based on gradients.	Water allocation optimization, river basin management.	[199]
Machine learning and water resource allocation	Actor–critic methods	Combines actor and critic networks to balance exploration and exploitation in water resource management.	Water allocation decision making, adaptive control.	[200]
Reinforcement learning and environmental policy	Proximal policy optimization (PPO)	Employs the PPO algorithm to optimize water resource management policies while ensuring stability.	Sustainable water resource management, policy optimization.	[201]
Machine learning and water resource allocation	Deep deterministic policy gradient (DDPG)	Utilizes deep reinforcement learning for continuous action spaces in water allocation problems.	Irrigation management, water distribution control.	[198]
Reinforcement learning and hydrological modeling	Monte Carlo methods	Estimates value functions and policies through episodic simulations in hydrological decision making.	Hydrological modeling, reservoir operation.	[202]
Machine learning and water resource management	Temporal difference (TD) learning	Learns from consecutive time steps to update value functions and improve water management strategies.	Water resource allocation, real-time decision making.	[203]
Reinforcement learning and water resource allocation	Asynchronous advantage actor–critic (A3C)	Utilizes asynchronous training for more efficient learning of water allocation policies.	Efficient water allocation, reservoir control.	[204]
Machine learning and water resource policy	Proximal value optimization (PVO)	Optimizes value functions and policies for water resource management in a stable manner.	Sustainable water policy development, adaptive control.	[205]
Reinforcement learning and environmental management	Soft actor–critic (SAC)	Enhances exploration in continuous action spaces of water management problems for better policies.	River flow control, ecological preservation.	[206]
Machine learning and water allocation	Twin delayed deep deterministic policy gradient (TD3)	Extends DDPG to improve stability and convergence in water allocation problems.	Water distribution optimization, adaptive control.	[207]

2.5. Evaluation Methods and Performance Metrics in ML

ML approaches can produce different outcomes, making it crucial to assess their performance based on the achieved results. Various statistical evaluation measures have been proposed to gauge the effectiveness of ML prediction techniques. In Table 9, we present a summary of commonly used evaluation metrics, categorized as magnitude, absolute, or squared error metrics.

Magnitude metrics include mean normalized bias and mean percentage error, which quantify the disparities between predicted and observed values. These metrics offer insights into the magnitude of deviations.

For cases where the focus is solely on the deviation from the norm, absolute error metrics can be employed. These metrics report the absolute error as a positive value, using observed (Y), predicted ($\hat{Y}$), mean of observed ($\bar{Y}$), and mean of predicted ($\bar{\hat{Y}}$) values.

Squared error metrics, such as mean squared error and root mean squared error, emphasize the squared differences between observed and predicted values. These metrics help in understanding the overall accuracy of the predictions, with higher values indicating larger errors.

Additionally, there are metrics like accuracy, precision, recall, and F1 score that are commonly used for evaluating classification models. Accuracy measures the proportion of correctly classified instances, while precision focuses on the proportion of true positives out of predicted positives. Recall quantifies the proportion of true positives out of actual positives, and the F1 score provides a balanced measure between precision and recall.

By employing these evaluation metrics, ML practitioners can assess the performance of their models, gaining valuable insights into their effectiveness and areas for improvement [125]. Table 20 illustrates the criteria used to evaluate prediction models. These criteria are fundamental in the realm of predictive modeling, providing a means to assess the accuracy and effectiveness of various models in their predictive capabilities. They represent vital tools in the process of model assessment, aiding researchers and practitioners in making informed decisions regarding the quality and reliability of their predictive models.

2.6. Bibliometric Analysis and Search Method for the ML Methodologies

A bibliometric study offers an overview that is useful for outlining a research field's organizational structure and linkages to other fields. Furthermore, when analysis is performed using word statistical analysis tools, potential research trends, hotspots, and the direction of science can be determined. The Scopus database was selected due to its extensive collection of peer-reviewed literature and numerous tools that enable citation analysis, data export for additional research, and visual mapping.

Although the research is biased towards English publications and ignores nonindexed journals and grey literature, we think this still offers a useful, if constrained, summary of the new literary trends. Additionally, we think that a key component of the bibliometric study is the search technique. By lowering false positives and false negatives, the search terms are refined with the goal of guaranteeing that pertinent articles are included in the study.

A preliminary search for the key phrase “machine learning methodologies” (title/abstract/keyword search) generated 17,112 results. In terms of time period, all searches were not time-restricted since there are many older methods that are still used currently. While “machine learning”, “supervised machine learning”, “unsupervised machine learning”, clustering, classification, “semisupervised machine learning”, etc. appeared prominently, there were cases such as “reinforcement learning” and “association rules” that hardly featured in the top keywords. Even when considering only methodology-related keywords, then “uncertainty analysis”, “regression analysis”, and “mathematical models” were the more common keywords and not the previous ones.

Table 20. Performance criteria for prediction model evaluation [208,209].

Metric.		Description
Mean normalized bias error	$MBE = \frac{1}{n} \sum_{i=1}^n \frac{Y_i - \hat{Y}_i}{Y_i}$	Estimation of the average bias of the prediction approach used to decide on measures for correcting the approach bias.
Mean percentage error	$MPE = \frac{1}{n} \sum_{i=1}^n \frac{Y_i - \hat{Y}_i}{Y_i} \times 100$	The average percentage error, calculated by comparing the forecasts of a model with the actual values of the quantity being predicted.
Mean absolute error.	$MAE = \frac{1}{n} \sum_{i=1}^n \hat{Y}_i - Y_i $	The mean absolute error (MAE) is a statistical measure that evaluates the average magnitude of errors in a set of forecasts, irrespective of their direction.
Mean absolute percentage error	$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{Y_i - \hat{Y}_i}{Y_i} \times 100$	The accuracy rating metric assesses accuracy as a percentage by calculating the average absolute percentage error minus the actual amounts divided by the actual amounts.
Relative absolute error	$RAE = \frac{\sum_{i=1}^n Y_i - \hat{Y}_i }{\sum_{i=1}^n Y_i - \bar{Y} }$	A relative performance metric used to evaluate the effectiveness of a prediction model.
Weighted mean absolute percentage error	$WMAPE = \frac{\sum_{i=1}^n Y_i - \hat{Y}_i }{\sum_{i=1}^n Y_i }$	A weighted version of the mean absolute percentage error (MAPE) that serves as a measure of prediction accuracy for a forecasting method.
Normalized mean absolute error	$NMAE = \frac{MAE}{\frac{1}{n} \sum_{i=1}^n Y_i }$	A metric designed to facilitate the comparison of datasets with varying scales in relation to the mean absolute error (MAE).
Mean squared error	$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$	This metric quantifies the discrepancy between the mean squares of the actual and forecasted values.
Root mean square error	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2}$	An estimation of the average error magnitude.
Coefficient of variation	$CV = \frac{\sqrt{\frac{\sum_{i=1}^n (Y_i - \bar{Y})^2}{n}}}{\bar{Y}}$	The relative standard deviation is a standardized measure that quantifies the dispersion of a probability distribution.
Normalized root mean square error	$NRMSE = \frac{RMSE}{Y_{imax} - Y_{imin}}$	A normalized root mean square error (RMSE) that enables comparisons between datasets and models with different scales.
Coefficient of determination	$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2}$	A metric that measures the variance ratio of a dependent variable with respect to an independent variable.
Willmott's index agreement	$WI = 1 - \left[\frac{\sum_{i=1}^n (Y_i - \bar{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y}_i + \hat{Y}_i - \bar{Y}_i)^2} \right]$	A metric that measures the ratio between the mean square error and the potential error.
Legates–McCabe's	$LM = 1 - \left[\frac{\sum_{i=1}^n Y_i - \hat{Y}_i }{\sum_{i=1}^n Y_i - \bar{Y}_i } \right]$	A robust alternative metric for evaluating goodness-of-fit or relative error that addresses the limitations of correlation-based metrics.
Kling–Gupta efficiency	$KGE = \sqrt{[r - 1]^2 + [\alpha - 1]^2 + [\beta - 1]^2}$ $r = \frac{cov(\hat{Y}, Y)}{\sigma(\hat{Y}) \cdot \sigma(Y)}, \alpha = \frac{\sigma(\hat{Y})}{\sigma(Y)}, \beta = \frac{\bar{\hat{Y}}}{\bar{Y}}$	This metric assesses model efficiency by considering accuracy, precision, and consistency components. It incorporates the correlation coefficient (r), bias (α), and variance ratios (β) between predicted and observed values, with σ representing the standard deviation.
Akaike information criterion	$AIC = -2 \log \left(L \left(\theta^{ML} Y \right) \right) + 2_i$	This measure evaluates model performance while considering model complexity. It utilizes the vector of maximum likelihood estimates of the model parameters (θ ^{ML}) and the number of observed values (i).
Probabilistic Metric		Description
Continuous ranked probability score	$CRPS = \int_{-\infty}^{+\infty} [P(\hat{Y}_i) - H(\hat{Y}_i - Y_i)]^2 d\hat{Y}_i$	This metric quantifies the quadratic difference between the forecasted and empirical cumulative distribution functions (CDF). It involves the prediction CDF (P($\hat{Y}_i$)) and the Heaviside step function (H), which equals 0 if the forecasted value ($\hat{Y}_i$) is less than the observed value (Y_i), and 1 otherwise.
Average width of the prediction intervals	$AWPI = \frac{1}{n} \sum_{i=1}^n (\hat{Y}_i^u - \hat{Y}_i^l)$	This is an estimation of an interval, with a specified confidence level, within which a future observation is expected to fall based on prior observations. The upper and lower bounds of the 95% prediction interval are denoted by u and l, respectively.
Prediction interval coverage	$PICP = \frac{1}{n} \sum_{i=1}^n c_i, c_i = \begin{cases} 1, & \text{if } Y_i \in [\hat{Y}_i^l, \hat{Y}_i^u] \\ 0, & \text{if } Y_i \notin [\hat{Y}_i^l, \hat{Y}_i^u] \end{cases}$	The proportion of instances in a holdout set for which the prediction interval successfully captures the actual value.
Prediction interval normalized average width	$PINAW = \frac{1}{n} \sum_{i=1}^n \frac{\hat{Y}_i^u - \hat{Y}_i^l}{R}$	This metric quantifies the width or extent of the prediction interval. The range of variation of the observed value (R) is used to determine the width of the interval.

In order to arrive at the set of articles within the intersection of ML methodologies and water management in general, we integrated the two search terms into one. To cast a wider net and ensure minimal articles were systematically filtered out from the search, the most prominent keywords were generated in the “water resource” keyword search, as discussed

in Section 3 later on in a separate bibliometric discussion. The vast majority of records were removed before screening. Specifically, 5523 records were duplicates, 4993 records were marked as ineligible by automation tools, and 4527 records were removed for other reasons. From the remaining 2069 records, 768 were excluded, creating 1301 reports which were sought for retrieval.

However, out of the legitimate reports, 784 were not able to be retrieved, resulting in 517 reports which were assessed for eligibility. From the number of the 517 elements, (a) 257 articles were not accessible due to restricted access rules to the journal sites, (b) 75 articles presented methodological incompatibility, and (c) 60 articles were off-topic findings, leaving, finally, a number of 125 articles that were included in this study, with 85 of them being actual reports of the included studies. The following PRISMA diagram (Figure 2) depicts our findings.

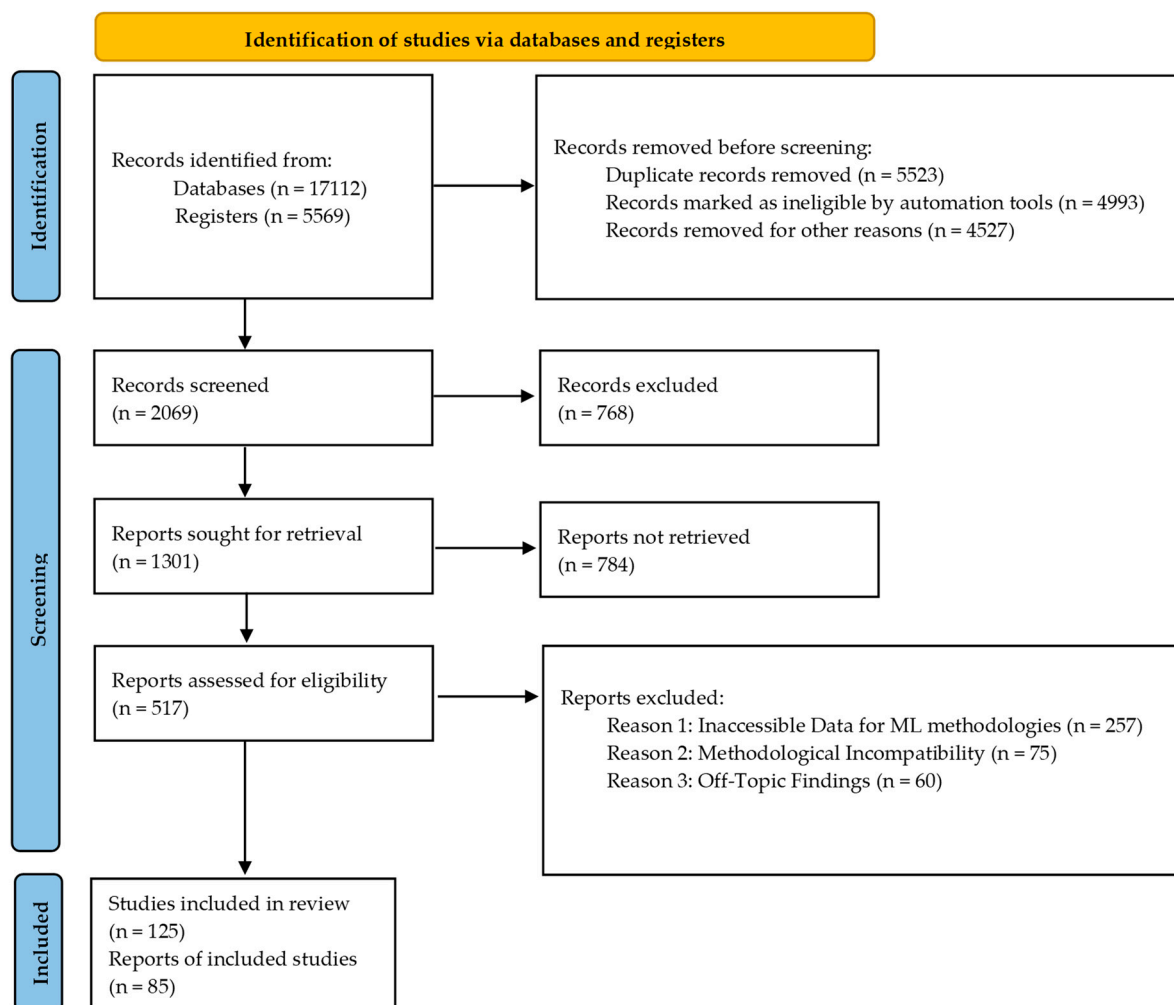


Figure 2. PRISMA analysis flowchart for the bibliometrics of the “machine learning methodologies”.

3. Using ML for Water Activities

From the late twentieth century to the present day, the rate of land use and land cover change (LULC) has been steadily increasing, primarily driven by uncontrolled population growth and economic and industrial development, especially in developing countries [210]. Desirable quality and quantity of water resources are essential for human survival and sustainable development. With a continuous increase in population, the demand for water is rising in tandem. ML plays a crucial role in managing, interpreting, and analyzing water resources. ML can predict water quality, map groundwater contaminants, classify water resources, detect contaminant sources, assess contaminant toxicity in natural water

systems, model treatment techniques, aid in characterization analysis, facilitate drinking water purification and distribution, and assist in wastewater collection and treatment in engineered water systems [211]. Determining and managing water quality are crucial for human wellbeing, but challenges arise from human errors. ML applications have become important in facilitating these processes, as demonstrated by successful integration into public systems and detailed investigations on shared datasets in water research [212]. Water resources management planning emphasizes the importance of careful planning and forecasting hydrological parameters like rainfall, runoff, solar radiation, groundwater, and evaporation for effective water resource management [213].

Mapping of the area of interest is carried out by applying remote sensing [214]. Through remote sensing, crop disaster monitoring, urban planning, and water resource management can be achieved. The creation of a thematic map from the satellite images of the area is achieved by image classification. In order to perform water detection from satellite images, software must be developed that uses multiple spectral bands to enable parallel image classification using supervised or unsupervised learning. The information obtained from the analysis can be used in protected natural areas to monitor water behavior over time [214]. High-resolution remote sensing techniques, also through big data and ML technologies, have the potential to impact many aspects of environmental and water management (EWM). Based on these, weather forecasting, disaster management, and the creation of smart water and energy management systems can be achieved. ML, like DL, tries to simplify as much as possible the difficulty of interpreting big data, due to the huge amount of information, by developing powerful algorithms and thereby extracting hierarchical features from the data [215]. Algorithms such as random forest (RF), support vector machine (SVM), artificial neural network (ANN), fuzzy adaptive supervised coordination theory and predictive mapping (fuzzy ARTMAP), spectral angle mapper (SAM), and Mahalanobis distance (MD) are capable of evaluating the accuracy through the use of kappa coefficient, RoC, and root mean square error (RMSE) [210]. Exploration of the potential applications of big data in the field of water resource engineering is the central focus. This inquiry encompasses an in-depth analysis of the merits and demerits associated with the utilization of big data techniques. Additionally, a succinct overview of the pertinent literature and empirical case studies is provided. Ultimately, it is postulated that the adoption of big data methodologies has the capacity to significantly enhance the precision and effectiveness of engineering solutions within the domain of water resources. The proposal of implementing a platform-based big data system for sharing critical data is highlighted, enabling the production of high-value and reliable information through the rapid processing of large and diverse datasets. The work underscores the necessity of establishing standard operating procedures to preclude and address computational errors and malfunctions inherent in big data applications [216].

Water has a direct relationship with energy and food. Modeling and analysis of the energy, water, and food (EWF) relationship is performed with static, deterministic models that facilitate decision making for well-behaved and predictable resource systems over time. These frameworks, however, are partially limited in their functionality since they do not take into account the exposure of systems to the dynamic nature of exogenous uncertainties and associated risks at the interface. Through reinforcement learning based on sequential decision making called Markov decision process (MDP), design and control can be applied that could help achieve adaptive systems under unstable conditions with the aim of maximizing economic output and improving their operational resilience [217].

Another crucial aspect to address is data control. The collected data may sometimes be incomplete or noisy, resulting in missing features. Therefore, additional data samples are required to extract useful supervised or unsupervised classification methods. This issue can be addressed by decomposing the signal to compute missing features (data augmentation), classifying noisy samples, and artificially generating new data samples (data augmentation). ML plays a vital role in applications such as brain–computer interfaces, epileptic classification of intracranial electroencephalographic signals, face recognition/verification,

and water network data analysis [218]. In terms of the urban sector, the use of hot water in homes plays a dominant role in people's lives, especially in winter periods. In recent years, renewable energy sources, such as wind and photovoltaic generation, have been increasingly applied, which has led to some problems in power systems, such as the duck curve and unreliability due to environmental variability [219]. An effective solution to this problem is demand response (DR). Learning hot water usage behavior allows water heating systems to continuously adapt to stochastic demand and reduce energy consumption. Electric water heaters (EWHs) are considered ideal candidates for DR due to their ability to store energy. Through ML, several objectives can be achieved, such as the following: 1. To determine the state of the art for energy optimization and scheduling of EWHs by creating smart grids and smart buildings; 2. To be able to predict the stochastic behavior of domestic hot water (DHW) demand and explore the potential energy use reduction by an adaptive system—smart dynamic simulation system for hot water use. ML models, such as random forest, multilayer perceptron, long short-term memory neural network, and LASSO regression, can be used in both classification and regression [220].

Another problem that households have to face is frequent attacks on water supply facilities, because this way, water distribution systems (WDSs) are deregulated [221]. To address this problem, it is proposed that in addition to traditional solutions such as data encryption and authentication, it is proposed to detect attacks on WDSs to reduce the cases of disruption. The attack detection system should meet two critical requirements: high accuracy and near-real-time detection. To achieve these two requirements, we can use self-predictive and unsupervised algorithms for attack detection in the cyberphysical domain (CP). For high accuracy, heuristic adaptive self-predictive algorithms are applied for near-real-time decision making and detection sensitivity. Unsupervised algorithms attempt to detect the attacks to maintain high detection accuracy as much as possible using isolation forest [221]. Based on the problems mentioned above, the World Health Organization has taken actions on water safety plans (WSPs), which involve holistic assessment and risk assessment. For proper water management and water quality, drinking water suppliers should also take the income of the residents into consideration. Many countries and regions lack case studies, legal requirements, and educational resources for WSPs, corresponding to widespread capacity deficiencies in the water sector. For this reason, a taxonomy of WSP training through ML is proposed [222]. Renewable energy sources have the potential to be converted into different types of energy. For example, solar energy can be converted into chemical energy in addition to thermal energy with the help of ML. ML contributes to the acquisition of detailed scientific knowledge about the underlying principles governing light-harvesting phenomena and can accelerate the fabrication of light-harvesting devices [223]. Supervisory control and data acquisition (SCADA) systems play an important role in providing remote access, monitoring, and control of critical infrastructure (CI), including power systems, water distribution systems, nuclear power plants, etc. The increasing interconnectivity, standardization of communication protocols, and remote accessibility of modern SCADA systems have massively contributed to the exposure of SCADA and CS systems to various forms of security. Any form of intrusive action on SCADA units and communication networks can create catastrophic consequences for nations due to their strategic importance to CS operations.

Therefore, prompt and effective detection and classification of intrusions in SCADA systems hold great importance for the operational stability of national CSs. Through supervised learning techniques, intrusion solutions for SCADA can be found [224]. The challenges facing agriculture are multifaceted and multifactorial. Mainly, problems arise in crops due to the unpredictable nature of climate change, water, and pests [225]. To be able to maximize crop yields, appropriate assessments of microclimate parameters need to be implemented at the commercial scale for indoor and emission-free farming. This is achieved using Internet of Things (IoT)-based sensors. To select the appropriate model for microclimate parameter assessment using IoT sensors, a comparison is made between greenhouse crop production systems as well as the outdoor environment. With

this analysis, a better environment for cultivation can be achieved and, thus, productivity can be increased. The supervised learning algorithm offers self-adjusting reference inputs based on the selected crop. Solar radiation, water vapor pressure deficit, relative humidity, temperature, and soil fertility are the raw data processed using the appropriate model. Also, various growth stages such as light conditions and timeframes are considered to determine the reference limits for categorizing the variation in each parameter. The microclimate parameters can be dynamically estimated using the Simulink model and IoT sensor nodes [225]. The models used for crop improvement, yield prediction, crop disease analysis, and water stress detection are random forest (RF), which is a supervised ML algorithm [226], decision trees, support vector machines, Bayesian networks, and artificial neural networks. These methods enable the analysis of soil, climate, and water regime, which are significantly involved in crop development and precision agriculture [227].

In water treatment, AI techniques like ANN, DNN, gradient boosting, and random forest regression have been used. Multivariate LSTM models generate valuable data, and data preprocessing methods like interpolation and anomaly detection are explored. The random forest regression algorithm excels, accurately predicting MIW parameters like Fe and acidity over 60 days. This underscores AI's role in optimizing water treatment and the need for rigorous statistical analysis in model development [228].

The prediction of removal of different types of water pollutants is also carried out using ML algorithms. The combination of different ML techniques such as multilayer perceptron, artificial neural network (MLPANN), least square support vector machine (LS-SVM) method and feedforward backpropagation neural network (FFBPANN) were most effective for analyzing water quality and predicting the performance of different water treatment processes. Therefore, hybrid ML models are more suitable for interpreting and addressing these challenges [229]. Moreover, it is equally vital to comprehend the trends in both quantity and quality of produced water (PW) within the oil and gas industry for effective management. A recent study delved into this by analyzing historical data from the New Mexico portion of the Permian Basin. ML algorithms were employed, with the random forest regression model demonstrating remarkable accuracy in predicting PW quantity. Additionally, the autoregressive integrated moving average model yielded satisfactory results in forecasting PW volume as a time series. The examination of water quality revealed intriguing insights; PW samples from the Delaware and Artesia Formations exhibited the highest and lowest average total dissolved solids concentrations, measuring 194,535 mg/L and 100,036 mg/L, respectively [230]. Furthermore, a comprehensive assessment of AI techniques applied in river streamflow forecasting revealed a dual-wave evolution. These AI models have made substantial strides in augmenting the accuracy of streamflow predictions, albeit with challenges such as overfitting and prolonged learning. The subsequent wave introduces innovative hybrid models and ensemble techniques, promising enhanced data processing efficiency and suggesting prospective research directions [231].

ML-based forecasting models have shown promise in assisting reservoir operators with releasing water during heavy rainstorms and conserving water during drought seasons. The evaluation of various models using performance metrics such as mean absolute error and R-square suggests that VARMAX performs best, indicating a seasonal component in the dataset, while ARIMA struggles to produce satisfactory results in the presence of a seasonal component. The MAE and RMSE values of both models support this argument [232]. Additionally, a study found that various machine learning models, such as Boosted Decision Tree Regression (BDTR) and Bayesian Linear Regression (BLR), performed well in predicting water levels, offering potential benefits for reservoir management. Further research should consider additional input parameters, including climate-induced rainfall changes [233].

For water resource management, power generation, and drought prevention, the accurate forecasting of water levels in reservoirs is of great importance. Hybrid meta-heuristic algorithms, including ANN, ANFIS, BA, COA, and SVM, have been employed to identify factors and challenges in water level prediction from 2000 to 2020 [234]. To

improve water management planning in drought-prone regions like the American West, the results show that RF provides the most accurate results and reduces modeling run times, enabling exploration of future climate changes and drought conditions [235]. Forecasting water levels is a critical task in disaster prevention, and while physically based models have historically been effective but computationally expensive, data-driven models like statistical ML methods and the ARIMA model offer cost-effective solutions with improved performance [236].

Recent advancements in ML algorithms have significantly enhanced the ability to forecast the complex and dynamic process of lake water level fluctuations, which are challenging to predict accurately due to their nonlinear and stochastic nature [237]. In a related context, a real-time data analysis platform uses ML to predict water consumption. It employs a web-oriented architecture for better management and monitoring of water usage. The platform collects data, handles uneven time series, and employs learning capabilities for analysis and forecasting. Rigorous data checks and advanced methods like long short-term memory and backpropagation neural network ensure accurate predictions of water consumption levels and timings, even without prior knowledge [238]. The rapid proliferation of ML and data management has led to the expansion of ML applications across various engineering disciplines. This expansion is driven by the recognition of the world's water supply's growing significance in this century. As a result, extensive research has focused on applying ML strategies to integrated water resources management (WRM) [239]. A substantial amount of clean water is lost worldwide due to leaks, but smart water networks can decrease this wastage by reducing water production and purchase, as well as the energy needed for distribution and treatment, as exemplified by a leak management project in the UK that employs advanced metering infrastructure and innovative instruments for precise monitoring and data analysis using the AURA-Alert anomaly detection system [240].

In the field of water supply network optimization and management, accurate forecasting of water demand in urban areas is of great importance, especially in the context of Milan, Italy. The study evaluates several forecasting models for short- and long-term water demand forecasting in urban areas and investigates the potential enhancement achieved by incorporating a wavelet data-driven forecasting framework (WDDFF). The findings reveal that, overall, the incorporation of WDDFF improves the predictive ability of the models. The LSTM wavelet decomposition technique combined with the LSTM technique shows high accuracy, with an R^2 value exceeding 0.9 for short- and long-term urban water demand forecasts. In addition, the LightGBM model effectively reduces predictors and demonstrates the ability to predict and identify critical features in the field of hydrology and water resources [241].

In a multitude of studies, ML has proven to be invaluable in addressing diverse challenges in water resource management:

3.1. Water Resource Management and Quality Prediction

3.1.1. Water Resource Management Techniques

- **Irrigation optimization** [242]: XGBoost is harnessed to optimize irrigation scheduling, particularly in regions like Morocco, aiding in efficient water usage for crop cultivation.
- **Urban groundwater quality** [243]: Leveraging least squares support vector machines (LS-SVM), this study focused on enhancing the quality of urban groundwater. It effectively monitored and predicted groundwater quality, particularly in areas vulnerable to contamination due to urbanization.
- **Water level forecasting** [244]: Multiple ML models, including multilayer perceptrons (MLP), long short-term memory (LSTM), and XGBoost, were employed for accurate water level forecasting. These models contributed significantly to flood warning systems and freshwater resource management.

- **Superiority of MLP [245]:** Among the models used for water level prediction, MLP emerged as the standout performer. It exhibited a high degree of accuracy, especially in capturing short-term dependencies.

3.1.2. Flood Forecasting and Hydrological Models

- **Flood forecasting with TVF-EMD [246]:** A hybrid approach combining time-varying filtering with empirical mode decomposition (TVF-EMD) and ML techniques was employed for flood forecasting. This approach excelled in handling nonstationary time series data.
- **Mekong River water levels [247]:** Support vector regression (SVR) was applied to predict water levels in the Mekong River. SVR achieved a satisfactory mean absolute error, meeting stringent requirements for flood forecasting by the Mekong River Commission.

3.1.3. Water Demand Prediction and Climate Adaptation

- **Precise water demand predictions [248]:** Advanced ML techniques were utilized for accurate predictions of water demand in urban areas. These models underscored the significance of temporal dynamics in water usage patterns.
- **Vapor pressure deficit in Egypt [249]:** ML algorithms, including random forest (RF), were used to predict vapor pressure deficit (VPD) in different regions of Egypt. RF emerged as the top-performing model, supporting climate adaptation efforts.

3.2. Water Quality and Streamflow Management

3.2.1. ML Applications in Water Resource Management

- **Streamflow and water quality management [250]:** A novel approach was introduced for water resource management, addressing the nonlinearity and uncertainty of streamflow. The proposed hybrid model effectively predicted water quality and quantity, offering improved accuracy in capturing nonlinear characteristics.
- **Enhanced streamflow forecasting [251]:** With LSTM and metaheuristic optimization, we can improve streamflow forecasting. The results demonstrated significant enhancements in model performance, with the potential to support more effective flood management.
- **Smart farming in India [252]:** India's smart farming endeavors employed the Internet of Things (IoT) and ML classifiers, particularly the binary support vector machine (SVM). These technologies assisted farmers in optimizing crop irrigation, enhancing sustainability.
- **Urban water demand forecasting [253]:** Adaptive urban water demand forecasting was proposed, utilizing ML models to cater to changing consumption patterns and improving water resource management.
- **Cybersecurity in water infrastructure [254]:** Combining ML with operational metrics, this study enhanced cybersecurity measures in critical water infrastructure, addressing the increasing risk of cyberattacks in modernized water plants.

3.2.2. Water Management and Predictions

- **Water management simulations [255]:** Rule-based reservoir management models (RMM) were augmented with ML, specifically long short-term memory (LSTM), for reservoir simulations. These hybrid models improved accuracy and forecasting in large-scale water management.
- **ML in inland water science [256]:** This chapter explored the integration of ML with limnological knowledge, enhancing the accuracy and interpretability of models in inland water science, particularly in predicting water quality and quantity.
- **Waste separation for a circular economy [257]:** To combat environmental pollution, this study proposed waste separation techniques involving sensor-equipped con-

veyor belts. This approach contributed to recycling and organic manure production, promoting a circular economy.

- **Water demand prediction in Brazil [258]:** A novel hybrid model, combining support vector regression (SVR) and artificial neural networks (ANNs), excelled in predicting water demand for reservoirs supplying the Metropolitan Region of Salvador, Brazil. This advancement enhanced water resource management.

3.2.3. Advanced Predictive Models and Data Analysis

- **Water demand forecasting in urban areas [259]:** Hybrid models (WBANN and WANN) were developed for weekly and monthly water demand forecasting in urban areas with limited data. These models were more accurate, with improved reliability through wavelet analysis and bootstrap techniques.
- **Surface water electrical conductivity prediction [260]:** This study investigated surface water electrical conductivity (EC) prediction in the Upper Ganga basin. The random forest (RF) model outperformed others, showing improved accuracy and high correlation.
- **Data-centric water demand prediction [261]:** This study analyzed the impact of training data length, temporal resolution, and data uncertainty on water demand prediction. It was found that random forest (RF) and neural network (NN) models outperformed others, offering accurate short-term water demand forecasts.
- **Daily reservoir inflow prediction [262]:** This study explored daily reservoir inflow prediction using deep learning (LSTM) and ML (BRT) algorithms. LSTM demonstrated superior precision across various statistical measurements.

3.3. Advanced Techniques and Sustainability

3.3.1. Innovations in Water Resource Management and Forecasting

- **Optimizing agricultural irrigation [263]:** This study discussed the use of innovative technologies like UAVs, ML, and IoT to optimize irrigation in agriculture, improving water status monitoring and prediction.
- **Deep learning for agricultural water management [264]:** This study proposed a novel method using deep learning for feature extraction and classification in agricultural water management, achieving high accuracy and performance metrics.
- **Urban water demand forecasting with limited data [265]:** This study evaluated the effectiveness of extreme learning machine (ELM) models for daily urban water demand forecasting. The ELMW model achieved high accuracy, particularly in predicting peak demand.
- **Water demand forecasting in Kuwait [266]:** This study compared water demand forecasting methods in Kuwait, showing differences in accuracy between ARIMA and support vector linear regression models compared to actual consumption.

3.3.2. Advancements in Water Management and Quality Assessment

- **Intelligent water management system [267]:** This study proposed an intelligent system for optimizing water collection and distribution, including water consumption prediction, without specific performance metrics.
- **Water quality index prediction [268]:** This study developed water quality index (WQI) prediction models using water samples from North Pakistan. Hybrid algorithms showed superior performance with high accuracy and low error metrics.
- **Dynamic time scan forecasting (DTSF) [269]:** This study introduced the DTSF method for water demand forecasting in urban supply systems, demonstrating comparable or better predictions with fewer computational resources.

3.3.3. Role of Artificial Intelligence and Deep Learning in Water Research

- **Deep learning in water sector research** [270]: This study reviewed deep learning methods in the water sector for various tasks, serving as a roadmap for future challenges in water resources management.
- **Factors affecting nonrevenue water (NRW)** [271]: This study classified factors affecting NRW in water distribution networks, offering a systematic approach for management.
- **AI in river water quality assessment** [272]: This study reviewed the use of AI models in river water quality assessment, highlighting the need for handling missing data and implementing early warning systems.

3.4. Reservoir and River Quality Management

3.4.1. Innovations in Water Resource Management and Quality

- **Reservoir operation optimization** [273]: This study presented a classification system for organizing literature on reservoir operation optimization, providing practical recommendations.
- **Soft computing for water quality index (WQI)** [274]: This study developed a WQI using soft computing techniques, with ANFIS demonstrating reliability for WQI prediction.
- **Groundwater quality assessment in Sri Lanka** [275]: This study assessed the quality of groundwater for irrigation in Sri Lanka's tank cascade system, suggesting suitable areas.
- **Combating reservoir sedimentation** [276]: This study categorized strategies for combating reservoir sedimentation, offering a checklist for evaluating sediment management options.
- **Underground water level prediction** [277]: This study utilized a hybrid model to predict underground water levels in Khuzestan province, achieving high accuracy in water resource modeling.
- **River water quality modeling** [278]: This study utilized AI models to predict river water quality index (WQI) based on water quality variables. H₂O deep learning and random forest models were effective, especially for small catchments.
- **Superabsorbent hydrogel (SH)** [279]: This study explored the application of superabsorbent hydrogel (SH) in agriculture and slow-release fertilizers and discussed nutrient release mechanisms, highlighting the potential for sustainable agriculture.
- **Urbanization and groundwater quality** [280]: This study examined the impact of urbanization and land use on groundwater quality in Xi'an City, China, supporting sustainable urban development and groundwater management in Xi'an City.
- **Leakage detection** [281]: This study focused on efficient leakage detection in water distribution systems and emphasized the importance of enhancing operational efficiency and minimizing water losses.
- **ML in water systems** [282]: This study explored the application of ML in natural and engineered water systems and discussed the advantages and disadvantages of various ML algorithms for water-related issues.
- **Groundwater nitrate contamination** [283]: This study utilized ML techniques to predict nitrate concentrations in Mexico's groundwater and identified pollution hotspots and health concerns, emphasizing the need for sustainable agricultural practices.
- **Smart water management** [284]: This study discussed how smart water meters and data analytics improve urban water system design and highlighted enhanced efficiency throughout the water cycle.
- **River water quality prediction** [285]: This study developed ML models to predict river water quality and classify index values and achieved efficient prediction and classification of water quality index values.
- **Flow-regime-dependent streamflow prediction** [286]: This study proposed a flow-regime-dependent approach using various techniques to improve streamflow prediction, enhancing streamflow prediction for water resources management and planning.

- **Water use and management indicators** [287]: This study evaluated water use and management indicators based on sustainability criteria and identified indicators meeting sustainability criteria for informed decision making.

3.4.2. Factors Influencing Water Consumption and Water Quality

- **Household water consumption** [288]: This study proposed a framework for reviewing and analyzing the literature on determinants of household water consumption, aiding in prioritizing determinants for future research and practical recommendations.
- **Sürgü Stream water quality** [289]: This study evaluated the water quality of the Sürgü Stream in Turkey, assessed its impact on soil and crop performance, and provided insights into water quality index and suitability classes for irrigation.
- **Groundwater monitoring with ML** [290]: This study reviewed ML algorithms for groundwater monitoring and highlighted the effectiveness of ML in monitoring groundwater characteristics.
- **Water consumption in Qatar** [291]: This study analyzed factors affecting water consumption in Qatar and identified temperature and population density as key influences on water consumption.
- **Environmentally friendly toilets** [292]: This study developed a novel mechanism to reduce water consumption in toilets, aiming to make flushing more environmentally friendly, potentially conserving global water and energy.
- **Predicting water connection leaks** [293]: This study used ML to predict water connection vulnerability to ruptures and leaks. Models showed potential for effective distribution network management.
- **Corporate water management practices** [294]: This study examined the impact of macro factors on corporate water management practices, and identified factors driving water management practices for leading, average, and laggard companies.
- **Water quality parameter modeling** [295]: This study modeled water quality parameters in a river basin using regression models and provided water quality distribution maps based on watershed features.
- **Factors influencing domestic water consumption** [296]: This study analyzed factors influencing domestic water consumption in Joinville, Brazil. Socioeconomic and building characteristics play a significant role in water consumption.
- **Groundwater dynamics and prediction** [297]: This study used ML recharge. Rainfall was identified as a key influencing factor for groundwater recharge.
- **Energy-efficient underwater sensor networks** [298]: This study proposed an energy-efficient approach for underwater wireless sensor networks, utilizing clustering and routing techniques for efficient energy usage.
- **Groundwater management in arid regions** [299]: This study assessed groundwater management in Kebili's complex terminal aquifer and provided suitability classes for irrigation based on groundwater quality.
- **Model-independent leak detection** [300]: This study introduced a model-independent approach for placing pressure sensors in water distribution networks. It utilized genetic algorithms for leak detection without a hydraulic model.
- **Variable-rate irrigation (VRI)** [301]: This study explored the development of variable-rate irrigation (VRI) technologies for precision water management in agriculture. It highlighted the need for further research and practical support information.
- **Groundwater quality in Ojoto** [302]: This study assessed the quality of drinking groundwater in Ojoto, Nigeria, using pollution and ecological risk indices. It identified areas with contaminated water and suitability for drinking.

These clusters group the bullets based on their shared themes and topics, providing a more organized overview of the content.

3.5. Bibliometric Analysis and Search Method for Water Management

In this bibliometric study, the initial search for the keyword “Water Management” (utilizing title, abstract, and keyword fields) yielded a total of 4173 results. We did not impose any specific time restrictions during the searches as we recognized that older methods continue to hold relevance in the field, as we did previously with the bibliometric analysis of the ML methodologies. While conducting the analysis, we observed that keywords such as “Water Management”, “Groundwater”, “Reservoir”, “Water Quality”, “Irrigation”, “Water Demand Forecasting”, and others were prominent. However, certain terms like “river” and “evaporation” were less frequently encountered in the top keywords, even though they are equally important in the wider field of water management. Moreover, when focusing solely on methodology-related keywords, terms like “water resource assessment”, “efficiency analysis”, and “management models” were more prevalent compared to the others.

A significant number of records was excluded prior to the screening process. To be specific, 1523 records were identified as duplicates, 703 records were flagged as ineligible by automated tools, and 505 records were removed for various reasons. This initial culling left us with 1442 records that were further evaluated, and 627 were subsequently excluded, resulting in 815 reports that were sought for retrieval.

However, from the pool of legitimate reports, 494 could not be retrieved, leaving us with 319 reports to assess for eligibility. Among these 319 elements, (a) 37 articles were found to be irrelevant to the field of water management, (b) 58 articles contained outdated information, (c) 35 articles were not peer-reviewed, and (d) 15 articles were hindered by language barriers.

This process ultimately led to the inclusion of 174 articles in our study, with 106 of them representing the actual reports of the included studies. Our findings are depicted in the PRISMA diagram (Figure 3).

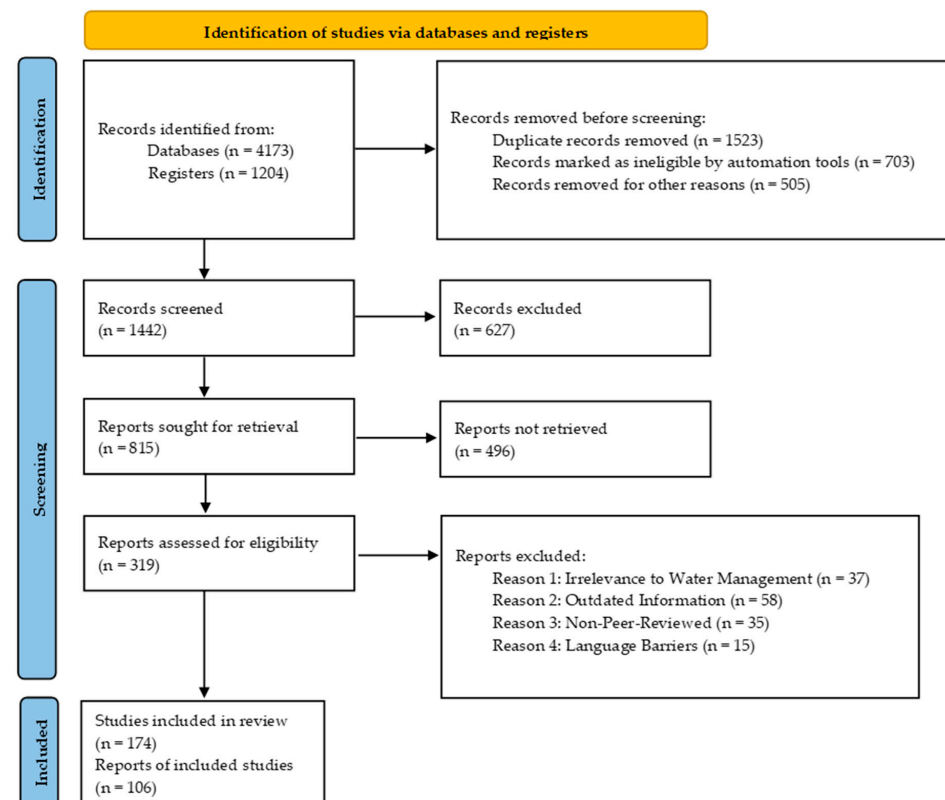


Figure 3. PRISMA analysis flowchart for the bibliometrics of the “Water Management” search.

4. Conclusions

This paper is a first exploration of the significant influence of ML methods in the field of the water management aiming to facilitate the monitoring, analysis, and optimization of water resources use. In a world grappling with escalating water scarcity and increasing demand, the convergence of technological innovation and scientific knowledge offers a glimmer of hope. The utilization of ML has revolutionized the landscape of water resource management. From predicting water quality and detecting pollutants to mapping underground aquifers and monitoring distribution systems, these tools shape a more sustainable future for water. Furthermore, the fusion of supervised and unsupervised algorithms, supported by the analytical prowess of deep learning, propels us towards intelligent decision making. Although there are many advantages of such an extensive survey, there are also disadvantages/limitations which are associated with this review.

In terms of advantages, this work consolidates information from various sources, highlighting trends, practices, and emerging techniques in water management using ML methodologies. It provides a knowledge synthesis, identifying gaps and issues for further investigation. It also intensifies interdisciplinary insights and approaches, serving as an educational resource for students, researchers, and practitioners interested in ML's application in water management. This foundational understanding makes it easier for newcomers to enter the field. Moreover, in our comprehensive exploration, we meticulously constructed tables that establish vital connections between diverse water management methodologies (distinct classification, regression, and other techniques). These tables offer invaluable insights into the practical applications of these methodologies and provide supporting references for verification, fostering a deeper understanding of the intricate field of water management. Overall, this extensive research covers the latest advancements in ML in connection to water management, aiming to maintain relevance despite potential outdatedness, balancing depth of analysis with breadth of coverage.

ML methodologies offer promising solutions in water management, but they face challenges such as data quality and quantity, interpretability and explainability, generalization, and integration with domain knowledge. Incomplete or inaccurate data can lead to unreliable predictions, affecting decision making in water management. Deep learning models are often considered “black boxes”, making understanding the reasoning behind model decisions crucial. Generalization is also a challenge, as ML models need to be able to make accurate predictions in new scenarios. Finally, integrating ML with domain-specific knowledge is essential for effectively addressing real-world water management problems. Addressing these limitations is vital to harness the full potential of ML in water management.

Future research directions in ML in water resource management include the development of hybrid ML models that combine various algorithms to improve water resource management predictions. The goal is to enhance the interpretability of ML models for transparency and understanding for stakeholders. The research can be applied to integrated water–energy management, urban water systems resilience, data and sensor integration, data privacy and security solutions, cost-effective AI solutions, stakeholder education and engagement, sustainable water resource governance, and climate change adaptation. Hybrid ML models can improve the accuracy and robustness of water resource management predictions. Explainable AI in water management can enhance the decision-making process for stakeholders. Advanced data fusion techniques can improve real-time monitoring and decision making in water resource management. Data privacy and security solutions can be addressed by researching ML-based methods for securing sensitive data while ensuring accessibility for authorized stakeholders. Future research should also explore sustainable water resource governance models and climate change adaptation strategies.

As the field evolves, researchers and practitioners must actively work to overcome these challenges and make ML methods more effective and applicable in real-world water resource management scenarios. The continuous pursuit of efficient water use through interdisciplinary approaches underscores our commitment to preserve this irreplaceable

resource for future generations. In subsequent work, we will focus on a comprehensive review of studies related to water management that have already been implemented, exploring potential enhancements aimed at better adaptation to our study area.

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