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Review

# Wetland Water-Level Prediction in the Context of Machine-Learning Techniques: Where Do We Stand?

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**Abstract:** Wetlands are simply areas that are fully or partially saturated with water. Not much attention has been given to wetlands in the past, due to the unawareness of their value to the general public. However, wetlands have numerous hydrological, ecological, and social values. They play an important role in interactions among soil, water, plants, and animals. The rich biodiversity in the vicinity of wetlands makes them invaluable. Therefore, the conservation of wetlands is highly important in today's world. Many anthropogenic activities damage wetlands. Climate change has adversely impacted wetlands and their biodiversity. The shrinking of wetland areas and reducing wetland water levels can therefore be frequently seen. However, the opposite can be seen during stormy seasons. Since wetlands have permissible water levels, the prediction of wetland water levels is important. Flooding and many other severe environmental damage can happen when these water levels are exceeded. Therefore, the prediction of wetland water level is an important task to identify potential environmental damage. However, the monitoring of water levels in wetlands all over the world has been limited due to many difficulties. A Scopus-based search and a bibliometric analysis showcased the limited research work that has been carried out in the prediction of wetland water level using machine-learning techniques. Therefore, there is a clear need to assess what is available in the literature and then present it in a comprehensive review. Therefore, this review paper focuses on the state of the art of water-level prediction techniques of wetlands using machine-learning techniques. Nonlinear climatic parameters such as precipitation, evaporation, and inflows are some of the main factors deciding water levels; therefore, identifying the relationships between these parameters is complex. Therefore, machine-learning techniques are widely used to present nonlinear relationships and to predict water levels. The state-of-the-art literature summarizes that artificial neural networks (ANNs) are some of the most effective tools in wetland water-level prediction. This review can be effectively used in any future research work on wetland water-level prediction.

**Keywords:** artificial neural network (ANN); anthropogenic activities; climate change; machine-learning techniques; urbanization; wetlands; water-level prediction

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## 1. Introduction

Wetlands are permanently or seasonally saturated with water. The Ramsar Convention defines wetlands as areas where water is the primary controlling factor in the environment and the plant and animal habitat of the wetland [1]. They play a crucial role in ecological systems. Wetlands are among the most productive ecosystems, also having multiple functions including flood attenuation, pollutant up-taking, recharge of the groundwater table, habitats for flora and fauna, water purification, stabilization of shorelines, water storage, carbon fixation, climate change mitigation, etc. Wetlands can trap sediment and heavy metals from surface runoff. Therefore, wetlands play an important role in nutrient retention and the purification of water while flowing through these ecosystems [2,3]. These ecosystems are more significant in ecological rejuvenation and contribute significantly to the conservation of biodiversity [4]. Therefore, it is a significant productive component of the environment [5]. Wetlands are important to mitigate climate-change impact [6]. They sometimes influence precipitation patterns and atmospheric temperatures [7]. The records showcase that the wetlands generally store 44 million tons of $CO_2$ per year globally [8]. In addition, they provide recreational opportunities [9]. Furthermore, two thirds of the global fish harvest is associated with the conditions of coastal and inland wetlands. Significant income is generated from the fish industry in most developing countries. Therefore, wetlands will be more prominent in socio-economic aspects [10].

Wetlands are considered one of the world's endangered ecosystems [11]. All over the world, wetland cover is being reduced due to urbanization and other human activities [12]. Wetlands significantly contribute to one of the land use types of the world, which takes around 6%. Therefore, their importance cannot be neglected in these sensitive areas. Nevertheless, threats and quality degradations of the wetland ecosystem can be observed due to environmental pollution and overexploitation [11]. Easy access to even conserved wetlands makes this degradation easier. Changes in the wetlands can be expected due to natural environmental fluctuations as well as human activities. Some of the anthropogenic activities are unintended due to poor knowledge and information. However, most anthropogenic activities that damage the wetland ecosystem are intended. A poor understanding of the importance of wetlands causes unintended damage, while negligence and less value given to wetlands cause intended damage [13]. Forming industrial zones is a significant anthropogenic contributor to the degradation of wetlands; therefore, many countries have now limited the use of these nearby areas of wetlands for industrial activities [14].

Maintaining the balance of the wetland ecosystem is highly important. The water level in a wetland is one of the important parameters to investigate, in addition to the quality of wetland water. The saturation of the wetland soil (hydrology) mainly determines how the soil, flora, and fauna develop. The richness of water within the ecosystem makes favorable conditions for the rapid growth of specially adapted plants (hydrophytes) and improves the quality of wetland (hydric) soil [15]. Therefore, wetland water-level prediction is important in several ways. Generally, wetlands have their own permissible water-level limits, whereas exceeding those limits can cause floods and other related environmental and hydrological issues [16]. Therefore, the wetland water levels reflect the general status of the wetland [17]. However, some countries still do not have a proper mechanism to map and monitor the water levels of the wetlands [18]. This could be due to the unavailability of measuring equipment as well as ignorance. However, some other countries have various ways to update their records on wetlands [19,20].

A Scopus database (www.Scopus.com; accessed on 20 April 2023) gives only 65 related research papers on wetland water-level prediction, which showcases the relatively insignificant attention. The search was carried out over 20 years as showcased in Figure 1. The recent trend in related research is quite appreciated, as it turns out 10 papers were published in 2022.

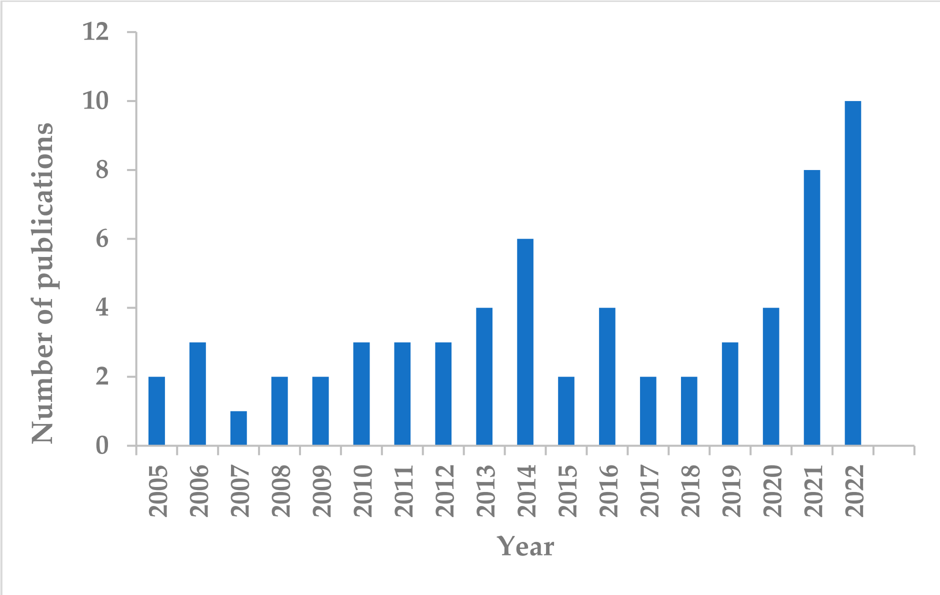
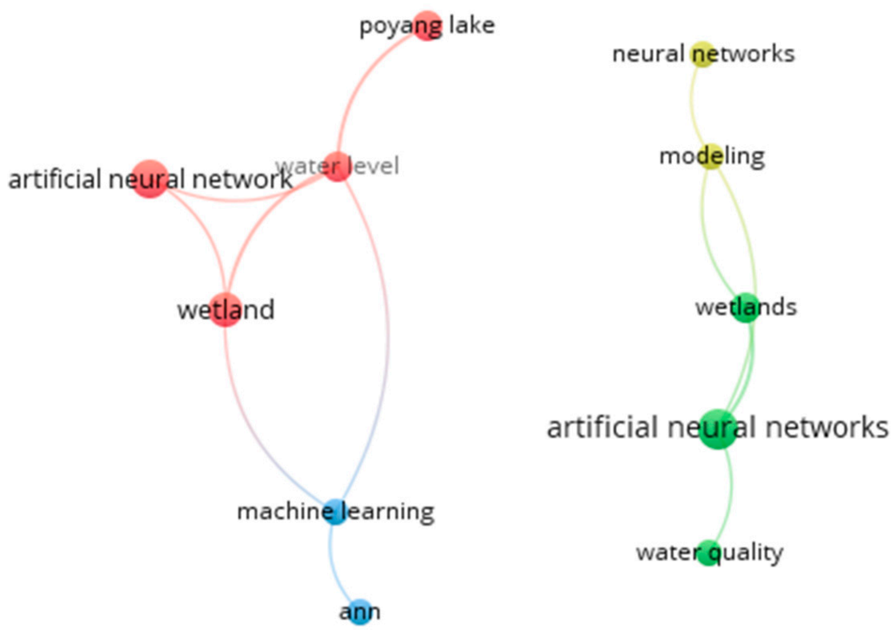


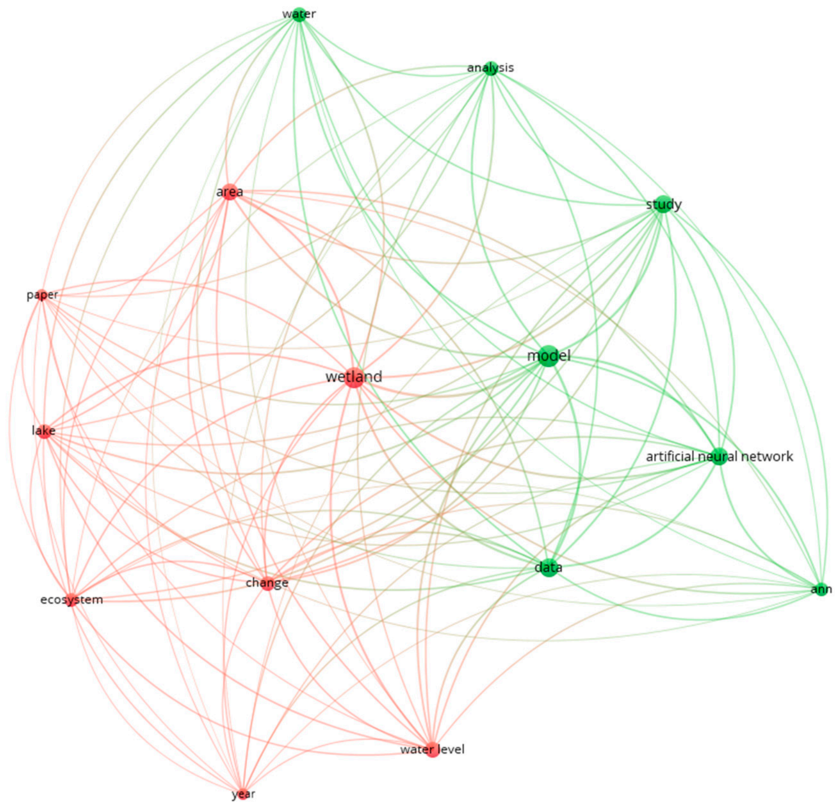

**Figure 1.** Variation of publications throughout the 2002–2022 period.

A bibliometric analysis of the search results proved the limited research on the prediction of water levels in wetlands using machine-learning techniques. It was found that out of 242 keywords tested, only 11 keywords appeared at a frequency of three times minimum for author keywords (see Figure 2a). Then, the keywords from abstracts were tested and it was found that the minimum number of occurrences of the term is 10. Figure 2 showcases the impact of less research in this area (refer to Figure 2b). Finally, the collaboration network was tested and the minimum number of documents per country was found to be three (refer to Figure 2c). In addition, it was revealed that out of 32 countries, only 9 met the thresholds.




(**a**)

**Figure 2.** *Cont*.




(**b**)


(**c**)

**Figure 2.** Bibliometric analysis: (**a**) Author keywords analysis; (**b**) Author keywords extracted from abstracts; (**c**) The collaborative country network.

Therefore, there is a greater requirement for a review of the prediction of water levels in wetlands using machine-learning concepts. Understanding this important gap in the research world, this paper extensively reviews the literature, highlighting the state of the art of techniques for the prediction of wetland water levels. The review should enhance the existing literature and then be used in any future research work.

## 2. Status of Wetlands in the World

The Ramsar Convention identifies 2414 wetlands that cover around 250 million hectares of the world. Due to its dynamic behavior and seasonal changes, a perfect area percentage for global wetland cover is difficult to measure (about 6%). However, different associations and researchers have estimated the wetland extent for different purposes. As per the United Nations Environmental Program (UNEP)—World Conservation Monitoring Center, the spatial coverage of the world's wetlands was estimated as 570 million hectares, which is around 6% of Earth's area [21]. Out of that 6%, lakes, bogs, fens, swamps, and floodplains comprise 2%, 30%, 26%, 20%, and 15%, respectively. However, the World Wildlife Fund, University of Kassel, Germany, and the Global Lakes and Wetlands Database (GLWD) showed that the global wetland extent was 10 million km$^2$ (1000 million hectares), which covers around 7% of Earth's surface [22]. Reis et al. [23] have tabulated the regional minimum estimates for wetland areas, and they are showcased in Table 1.

**Table 1.** Wetland Area [23].

| Region | Wetland Area (Km$^2$ $\times 10^6$) |
|---|---|
| Africa | 0.74 |
| Asia | 4.11 |
| Europe | 0.75 |
| South America | 0.89 |
| North America | 2.46 |
| Central America | 0.04 |
| Oceania | 0.17 |

The conversion of the wetlands into aquacultural fields, clearance of vegetation in wetlands, construction activities in wetlands, and illegal human settlements are some of the anthropogenic activities that damage wetlands [24]. Additionally, increased population growth and urbanization are two other major threats to wetlands [25]. The water quality in wetlands has been degraded due to insufficient inflows, poor quality of runoff water due to urbanization, and excessive agricultural water usage [26–28]. In addition, these reasons are not only impacting inland wetlands but also coastal wetlands. Researchers have shown that about 58% of the coral reefs are facing a moderate to high level of risk due to anthropogenic activities. On a global scale, 36%, 30%, 22%, and 12% of coral reefs in coastal wetlands are in danger due to overconsumption, coastal development, land-based pollution, and marine pollution, respectively [29]. In a recent example in the valley of Kashmir, it was observed that the conversion of agricultural lands into urban areas has become a prominent factor in increasing the loss of wetland cover [30]. Most of these wetlands are being used for dumping waste in both liquid and solid forms [31]. Although these wetlands are naturally used as flood-detention basins, the encroachment and the rapid urbanization happening in wetland zones reduce the water-holding capability while paving the way toward increasing flash floods [32].

According to Xu et al. [33], the major reasons for wetland degradation are pollution (54%), modification of natural systems (53%), use of biological resources (53%), and agriculture and aquaculture (42%). It was estimated that during the 1985 to 2010 period, the wetland loss rate was 16.57 mile$^2$/year (42.91 km$^2$/year) [34]. As a result of improper urbanization and rapid growth of population, approximately 91.2 km$^2$/year of wetland cover has lost between 1911 and 2004 [35]. Wetland management plans in various regions, particularly in Africa and Asia, still have a lot of room for improvement [33]. The wetland degradation rate was slightly reduced in the recent past, and that can be considered a positive approach; however, this could be due to some of the milder conservation policies driven recently. Nevertheless, a lack of good governance and management strategies and improper decision-making were identified as the major reasons behind this delineation [25]. Proper policies in wetland management, monitoring, restoration, knowledge and awareness, and advocate funding are among the five aspects suggested for the protection and restoration of the wetlands of the world [33].

## 3. Factors Affecting Wetland Water Level

Fluctuations in wetland water level are important for hydrological systems [36]. In addition, the chemical and biological attributes of soil, ecological behaviors of the wetland ecosystem, and root zones of wetland plants are also impacted by wetland water-level changes [37]. Therefore, understanding and quantifying the activities that affect water-level fluctuations in wetlands are essential [38]. Accordingly, hydrological and hydraulic conditions and behavior are important in assessing wetlands. Water flow rate to and from wetlands, the water level in wetlands, and inundation depths are significant parameters in these hydrological and hydraulic conditions [16]. The water level in wetlands mainly depends on the water-holding capacity of the wetland, inflows, and outflows. The water balance approach helps in determining which water transfer mechanisms are presented and the volume of water moving into and out of the wetland [39]. Precipitation (rainfall and snowfall), surface water inflows to the wetland, stream inflows, and groundwater inflows are the main inflows, whereas evapotranspiration losses, downstream streamflow from wetlands, and seepage losses are the main outflows of the wetlands. In addition, the variation of short-term water levels can happen as a reason for the antecedent moisture content in the soil. However, hydrological factors such as water table level and soil moisture ultimately determine how an external change affects the wetland itself [39]. Furthermore, vegetation dynamics can also be treated as a prominent factor in affecting wetland water levels [40].

The wetland water budget can be mathematically presented as per Equation (1). This is the well-known continuity equation in the water cycle [41,42].

$$\frac{\Delta S}{\Delta t} = (P + GWI + SRO + SI) - (ET + GWO + SO) \tag{1}$$

where $\frac{\Delta S}{\Delta t}$ presents the rate of change of storage (S and t stand for storage and time). P, GWI, SRO, and SI are precipitation, groundwater inflows, surface water runoff, and stream inflows, respectively, and are the inflows to the wetland. ET, GWO, and SO are evapotranspiration, groundwater outflows, and stream outflows, respectively, and are the outflows of the wetland. It is well understood that the wetland water levels as a height measurement have a direct relationship to the storage of the corresponding wetland. This is a widely used concept in hydrologic analysis.

The wetland water level is determined by hydro-climatic data such as precipitation, evaporation, relative humidity, temperature, wind speed, and hydrogeological data such as soil moisture, permeability, etc. [43]. The vegetation available in wetlands may be attached to the wetland bottom or float on water. Therefore, the water level can be used to determine the most suitable vegetation types for various wetland types. The fluctuation of the wetland water level can be called the wetland hydro pattern, and this pattern satisfies the continuity relationships of inflows and outflows [15]. Therefore, the wetland water level can be used to determine the status of wetlands as it affects the geomorphological, hydrological, and climatic conditions of the ecosystem and the surrounding environment [44,45].

Residential and commercial property development, their sewer and drainage networks, the extraction of minerals and peat for commercial purposes, and the construction of hydraulic structures such as dams and dikes affect wetland water levels [12]. These activities cause environmental changes such as erosion, subsidence, and hypoxia, all of which endanger the wetlands' long-term viability [26]. In tropical wetlands, ecological changes can also be observed, such as losses in salt marsh plants and seagrasses, as well as mangrove trees. Ecosystem services that are often overlooked are impacted by changes in the wetland ecosystem structure and its role. The loss of ecosystem services has an impact on human well-being as well as coastal wetlands' ability to regulate climate change [46].

## 4. Importance of Wetland Water-Level Monitoring

Wetlands are usually found in low-energy domains, resulting in slow water flowing. This is because the land surface in these areas is relatively level [47]. Because wetlands are found in relatively leveled terrain, their surface area can be expanded and contracted as the water level changes, allowing a large quantity of water to be stored [15]. Fluctuations in wetland water levels are an important scenario as it improves the productivity and the biodiversity of the wetland areas [48]. Water level, hydro patterns, and residence time are the three key elements that can be used to identify the hydrologic behavior of wetlands [15]. Subtle changes in water levels can have a significant impact on vegetation patterns, characteristics, and ecological processes in wetland habitats. Therefore, the water level and the associated vegetation cover can be used to determine water levels during drought, flooding, and normal conditions [49].

Wetlands are responsible for 20–25% of methane emissions into the atmosphere; however, they absorb a significant amount of carbon dioxide. Wetland water levels play a vital role in controlling methane emissions by functioning as an interface between aerobic and anaerobic processes and determining the degree of carbon dioxide production [50,51]. In addition, wetland water levels reflect the dissolved oxygen conditions in the wetland's soil–water system. The higher the wetland water level, the lower the dissolved oxygen concentration in the soil [15]. Anaerobic conditions are quickly developed in soils that are saturated rather than unsaturated soils, as the oxygen solubility in water is less. The amount and type of sediment–water nutrient exchange is affected by the frequency of water-level fluctuation, duration, and magnitude [52]. Therefore, the availability of water affects soil oxygen concentrations, which will adversely affect plant growth.

In addition, as a result of the water-level fluctuations, a direct impact on the plant and animal communities can be witnessed [53]. A case study done by Wilcox and Nichols [54] in the Lake Huron wetland has found that water-level fluctuations have an impact on the biodiversity and territory value of wetland plant communities. Therefore, water levels in wetlands are crucial to their survival and for the maintenance of the ecological balance of flora and fauna in wetlands. The species associated with wetlands have preferred water depths for their existence. Furthermore, some of the wetlands are situated along river basins and function as flood-detention basins. Those ecosystems generally fulfill a major task in managing flash floods that may happen due to extreme weather conditions. As such, water-level prediction and monitoring must be done to calculate the water-flowing depths downstream to prevent natural disasters such as floods [55]. Therefore, water-level measurement and forecasting will be more significant in wetland conservation and management [15,56]. It was observed that wetland water-level fluctuations are dependent on the seasonal and annual variation of climatic conditions. Therefore, evaluating water levels will be more applicable in forecasting varying climatic conditions from time to time [57]. For this purpose, models can be used to simulate and forecast wetland water levels when there will be a necessity to do so in decision-making relevant to wetlands or any other weather forecasting [36].

## 5. Available Machine-Learning Techniques to Predict Wetland Water Levels

Wetland water levels can be predicted in several ways, including physically based and data-driven approaches [58]. Physically based approaches can increase the level of complexity, are time-consuming to develop and require a high level of knowledge in the relevant field [16]. There are hydrologic and hydraulic models such as the Hydrologic Engineering Center's River Analysis System (HEC-RAS), the Soil & Water Assessment Tool (SWAT), and MIKE, which can be used to simulate water levels [59]. Nevertheless, the major drawback with those methods is that they need a proper understanding of hydrological processes and the variety of data related to inflows and outflows, bathymetry data, meteorological data, etc. [60]. Moreover, model development and calibration are more challenging when limited data are available [61]. However, machine-learning techniques can overcome most of these difficulties in predicting water levels in wetlands [62].

The data-driven machine-learning approach is a very effective technique, as it can be applied in many nonlinear scenarios such as water-level forecasting, sediment transportation, water-quality prediction, groundwater modeling, etc. [63]. Change in the water level is a complex hydrological phenomenon, as there are many controlling factors [64]. In such cases, decision-making is challenging. In contrast, traditional prediction techniques are incapable of achieving the desired research purposes with the unavailability of large-scale data [65]. Therefore, machine-learning techniques possess many advantages that include implementation simplicity, rapid running speed and convergence, and strong adaptability [66]. Therefore, the machine-learning technique is one of the ideal tools for most complex situations [16].

Artificial neural networks (ANN), kernel methods, radial basis function (RBF), and support vector machines (SVM) have mainly been identified as commonly used machine-learning techniques in water-level predictions [16,67,68]. However, hydrological predictions using computer-based models can produce uncertainties and the results can differ from model to model [69]. Therefore, selecting a convenient machine-learning technique is a challenging task because the purpose of different techniques is not similar. Typically, the availability of the data can be taken into consideration as the key element to construct a learning algorithm in wetland water-level predictions [70].

Artificial neural network (ANN) models are very effective for hydrologic systems, as they can build up relationships from the given data [71]. McCulloch and Pitts [72] were considered the pioneers of the concept of the artificial neural network [73]. They imitated the functions of the human brain which connects several neurons [74]. With weighted connections, these neurons are organized into two or more layers [75]. Figure 3 shows a simple architecture of an artificial neural network for wetland water-level prediction. It consists of three layers including an input layer, a hidden layer, and an output layer. The network is initially trained using the known hydrological parameters and known water levels. Then, the trained network can be used to predict the unknown wetland water levels using the known hydrological parameters. The number of hidden layers may be increased depending on the problem.

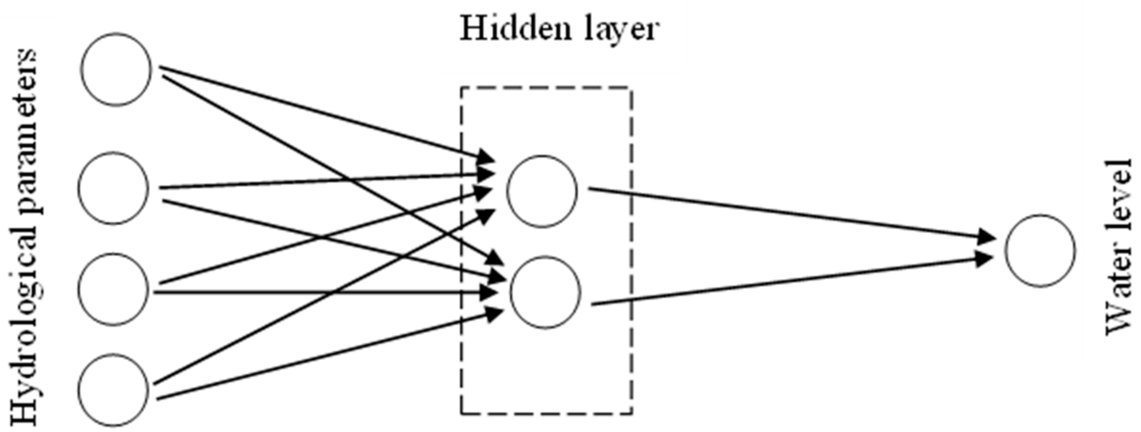



**Figure 3.** Layers in artificial neural networks.

The model runs to find the solution to the following mathematical function, which is time-dependent (refer to Equation (2)).

$$Y_t = \text{function}\ (X_{i,t}) \quad (2)$$

where Y is the dependent variable on time and $X_{i,}$ is the independent variable based on the time domain. The nonlinear relationship is formulated as per Equation (2) in ANN. Many optimization algorithms, including the Levenberg–Marquardt algorithm (LM), the scaled conjugate gradient (SCG) algorithm, the Bayesian regularization (BR) algorithm, etc. are used in enhancing the performance of the developed ANN model [76,77].

Support vector machine (SVM) is another popular machine-learning technique that can be used to predict water levels, which is based on artificial intelligence that has been developed on statistical learning theory [66]. The SVM identifies support vector hyperplanes that can linearly group the vectors of various classes with a maximum distant margin between them [16]. SVM operation is carried out with the assistance of kernels. Although the accuracy in the neural networks depends on the number of nodes in the hidden layer, the accuracy of the support vector depends on kernel mapping. Polynomial, sigmoid, and radial basis functions can be used in this manner [16]. Nevertheless, the radial basis function (RBF) can be considered the best kernel function used in water-level predictions, and it gives a globally optimal solution while avoiding overturning [78]. Equations (3) and (4) present the mathematical formulation of SVM in generic forms. The regression function used in SVM can be formulated as Equation (3).

$$\mathrm{Y} = \omega^{\mathrm{T}} \varnothing(\mathrm{X}) + \mathrm{b} \tag{3}$$

where $\varnothing(\mathrm{X})$ is a nonlinear function that is used to map the input vector to a high-dimensional space. $\omega$ is the weight vector and b is the bias. Minimizing the structural risk function (given in Equation (4)), the mapping function is estimated.

$$\mathrm{R} = \frac{1}{2}\omega^{\mathrm{T}}\omega + \mathrm{C}\sum_{i=1}^{N} L_{\varepsilon}(Y_i) \tag{4}$$

where $N$ is the sample size and C finds the tradeoff between model complexity and empirical error. $L_{\varepsilon}$ is Vapnik's $\varepsilon$ intensive loss function.

Random forests are another machine-learning approach and consist of a collection of "m" number of tree predictors. They are produced by randomly selecting the variables from separate categories [79]. Nevertheless, when there is a huge number of trees in the model, issues can be raised due to overfitting. This issue can be overcome by selecting the number of trees that gives the lowest mean square [16]. Random forests can operate not only with nonlinear data but also with non-Gaussian data. Additionally, the relative importance of each variable can be measured in this technique, which utilizes variable selections [80]. Some other features of random-forest models are that they are less sensitive to outliers and noise, provide useful internal estimates of error, are faster than bagging, correlation, strength, and variable importance, and are simple and easily parallelized [79]. This method was also applicable to many water-related studies, including wetland water-level prediction [81]. The schematic diagram of a generic random-forest approach is given in Figure 4. As stated, there can be n number of trees for decision-making. After combining all decisions, the final decision or result is estimated.

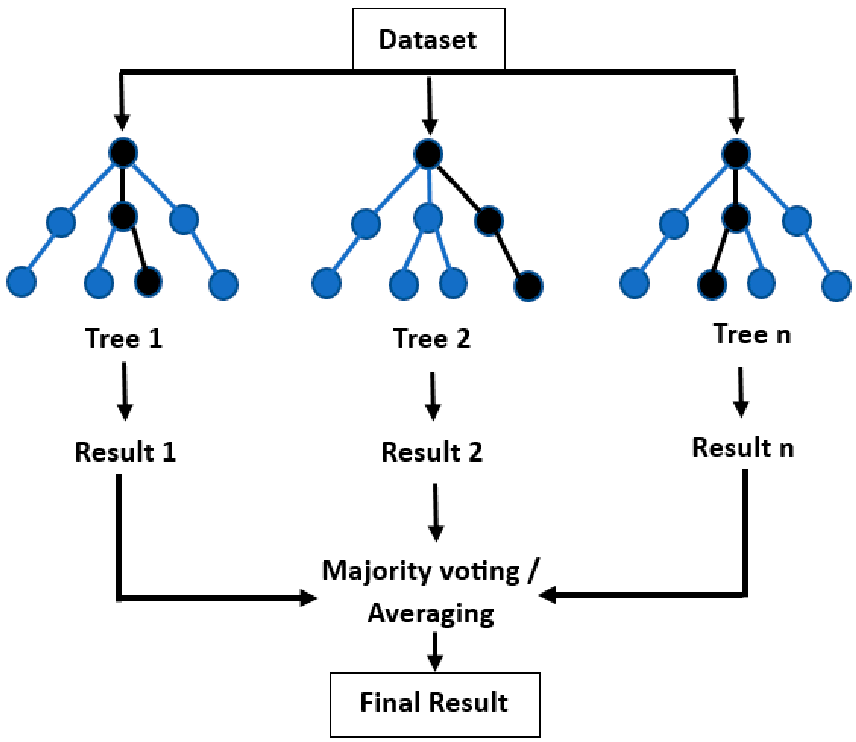



**Figure 4.** Schematic diagram of a generic Random-Forest approach.

## 6. Applications of Machine-Learning Techniques to Predict Wetland Water Levels

ANNs have been limitedly used in the water-level prediction of wetlands. However, there is a major challenge when it comes to seasonal and annual weather variations. Rezaeianzadeh et al. [43,82] predicted hourly water levels of wetlands in coastal Alabama. They used a combination of ANN and baseflow separation model to predict water levels and the prediction was successful. Even though the prediction of wetland water level is vital, there are many difficulties due to the limitation of the data [16]. Nevertheless, the water level of the Upo wetland in South Korea was predicted using several machine-learning techniques. This is the largest wetland in the country. Therefore, the results from the analysis are highly important to the country. Artificial neural networks, random forests (RF), decision trees (DT), and support vector machines (SVM) were used as the different machine-learning approaches [16]. The daily water levels for seven years (2009 to 2015) were predicted using the decision variables of meteorological data and upstream water levels. Prediction performance indicators showcased accurate water-level prediction.

The Sultan Marshes wetland water levels in Turkey were predicted by Dadaser-Celik and Cengiz [36]. This wetland is important as it is in the semi-arid region of the country. Climatic variables such as precipitation, evapotranspiration, and air temperature were used in their work. The root mean squared error (RMSE) and coefficient of determination ($R^2$) values were used to assess the accuracy of the developed model. The results of the analysis showcased the excellent applicability of machine-learning techniques in wetland water-level predictions. The wetland water levels in Lake Van, Turkey, were predicted by Altunkaynak [69]. Backpropagation algorithms were used in ANNs to train the model using known water levels. The prediction model illustrates accurate results with highly nonlinear relationships between rainfalls and water levels [69]. The above three stated prediction models used different techniques in training the neural network; nevertheless, they produced similar results in the context of the model performance. The authors also stated the computational complexity of the traditional models to investigate the wetland water levels and the possible higher relative error due to data limitations. Therefore, an error of less than 10% in a model based on machine-learning techniques can be accepted.

Furthermore, the ANN approach was used to investigate the variations in water level in Kerala Vembanad Wetland, India, by Gopakumar and Takara [83]. Other than the usual input parameters (rainfall and river discharges), wetland water levels on the preceding day were used as the input parameters for their model. Interestingly, the model was used to predict the water levels one day ahead. As usual, several numerical indices were incorporated in assessing the accuracy of the forecasting model. In addition, the authors suggested that the forecasting accuracy is low if the storage levels are incorporated into the forecasting model. Therefore, previous-day water levels minimize the errors as the water level indirectly represents the storage of the wetland.

A nonlinear regression model and an ANN model were used to predict the wetland water levels by Saha et al. [84]. They have taken an interesting approach using Landsat satellite images of the wetlands in the Atreyee River basin, India. The analysis was carried out during the pre- and post-monsoon seasons [84]. Even though both models performed accurately, the artificial intelligence method is better because it is a physical process-based model [84]. Karthikeyan et al. [85] have done a case study on groundwater level prediction in a riparian wetland on the tropical coast using artificial neural networks. They used two ANN architectures: the feed-forward network and the recurrent neural network. In addition, they also incorporated five algorithms to train the model. The water levels in a well in the study area were chosen for simulation purposes. Using performance indices, they also noticed that predicted water levels have fair accuracy.

Table 2 summarizes the main attributes of using ANN in wetland water-level prediction. All developed models have showcased higher performance in RMSE, Nash–Sutcliffe efficiency, and coefficient of determinations.

**Table 2.** Summary of literature on wetland water-level prediction using ANN.

| Reference | Wetland Location | Period | Data Resolution | Method | Accuracy |
|---|---|---|---|---|---|
| Rezaeianzadeh et al. [43] | coastal Alabama | February 2011 to March 2012 | Hourly | ANN | RMSE = 2.9 cm<br>Nash–Sutcliffe efficiency = 0.98 |
| Rezaeianzadeh et al. [82] | coastal Alabama | February 2011 to March 2012 | Daily averaged values from Hourly | ANN with SWAT model | RMSE = 14.5 cm |
| Choi et al. [16] | Upo Wetland, South Korea | 2009 to 2015 | Daily | ANN, DT, RF, SVM | $R^2$ = 0.96<br>Nash–Sutcliffe efficiency = 0.92<br>RMSE = 0.09 m<br>Persistence Index = 0.19 |
| Dadaser-Celik and Cengiz [36] | Sultan Marshes Wetland, Turkey | 1993 to 2002 | Monthly | ANN | $R^2$ = 0.96<br>RMSE = 4 cm |
| Altunkaynak [69] | Lake Van, Turkey | | | ANN | |
| Gopakumar and Takara [83] | Vembanad Wetland, India | 1996 to 1999 | Daily | ANN | $R^2$ = 0.87–0.9<br>RMSE = 5.63 cm–8.88 cm |
| Saha et al. [84] | Atreyee River basin, India and Bangladesh | 1987 to 2019 | Random (Water depth as a function of NDWI) | ANN | $R^2$ = 0.42–0.69 |
| Karthikeyan et al. [85] | Padre Wetland, India | July 2004 to May 2006 | Weekly averaged based on daily data | ANN | Normalized RMSE = 0.2335–0.4885<br>Relative RMSE = 1.4920–3.6418<br>Nash–Sutcliffe Efficiency = 0.7499–0.9538<br>Correlation Coefficient = 0.9225–0.9798 |

Nevertheless, a lot of examples of the application of SVM on hydrological predictions can be found in the literature. Support vectors have been used by several researchers for water-level prediction in wetlands and associated lakes, rivers, and reservoirs. Khan and Coulibaly [86] studied the applicability of the support vector machine (SVM) in the long-term prediction of lake water levels. They used the optimization technique in the SVM for parameter selection. The performance was compared with another two models, namely the multilayer perceptron and conventional multiplicative seasonal autoregressive model. They concluded that the support vector model has performed well while being competitive with the other two models. As stated in the previous section, Choi et al. [16] developed a water-level prediction model for the Upo wetland in South Korea. The Radial basis function was used as the kernel function for the SVM-based model and the optimal parameters were selected using 10-fold cross-validation.

Bafitlhile and Li [78] developed a water-level prediction model that represents a range of geo-climatic systems (humid, semi-humid, and/or semi-arid humid, semi-humid, and semi-arid). They stated that urbanization and climate change resulted in high runoff and, as a result, humid and semi-humid areas experienced frequent flood events, whereas semi-arid areas experienced flash floods. They used both ANN and SVM for the simulation and prediction of the water flow of the different wetlands. The comparison showed that both the neural network model and the support vector model performed reasonably in humid and semi-humid areas. Nevertheless, they suggested that support vectors are better than neural networks in water-level simulations. It was reported that models performed well for humid and semi-humid systems, while SVM performed better than ANN in the streamflow simulation of all catchments.

Wavelet support vector machines have played an important role too. Wei [87] successfully used wavelet SVMs to forecast hourly water levels during typhoon season. For modeling purposes, they used both classical Gaussian and wavelet SVMs. The developed models were applied to the water-level forecasting of the Tanushi River basin in Taiwan. Eleven important wetlands are connected to the Tanushi River basin [88]. The results showed that the accuracy and performance of the wavelet support vectors are better than Gaussian support vectors. In addition, Kisi et al. [67] studied the prediction of water-level variations in the Urmia wetland using SVM coupled with the firefly algorithm. Optimal SVM parameters were obtained using the firefly algorithm. They conducted a comparison of a support vector machines firefly algorithm with genetic programming and artificial neural networks. The experimental results demonstrated that the support vector machines firefly algorithm approach outperformed the other two models (genetic programming and ANN) in terms of predictive accuracy and adaptation to the given environment. Therefore, the use of support vector machines firefly algorithm models for water-level prediction is recommended.

Furthermore, Li et al. [89] compared streamflow forecasts using extreme machine-learning methods and random forests. They used five data-driven models: ANNs, SVMs, random forests, extreme-learning machines, and extreme-learning machines with kernels. The performance of the random-forest model was better than the other four models. When modeling low water levels, the extreme-learning machine with kernels showed accurate outputs. Therefore, they concluded that all five models have advantages as well as some shortcomings. Yang et al. [68] studied water-level prediction in a reservoir with a wetland downstream. The model was based on investigating a missing value followed by a variable selection. Modeling was carried out using random forests. The results of this study show that the performance of the random-forest model is outstanding when variable selection is carried out with all variables, rather than listing them. It can be concluded that any model's output depends on the proper selection of variables.

In addition, machine-learning techniques have been frequently used in various assessments of constructed wetlands [90]. Guo and Cui [91] applied machine-learning techniques (random forests and extra trees) to optimize the performance of the constructed wetlands and showcased a greater performance. Li et al. [92] used the backpropagation of an artificial neural network to improve the efficiency of nutrient removal from constructed wetlands. Therefore, there is a scope for applying machine-learning concepts to construct wetlands and to enhance the performance of wastewater treatment. Furthermore, similar techniques can be used in the tidal water-level prediction of nonlinear systems such as lagoons [93,94]. Therefore, machine-learning techniques can be effectively used in many nonlinear hydrological systems to enhance the performance of various aspects.

## 7. Summary of the Review

Limited research work on wetland water-level prediction using machine-learning techniques can be found in the literature. This has been confirmed by a Scopus-based search and a bibliometric analysis using the relevant keywords. Therefore, a review of wetland water-level prediction as a function of climatic parameters is a gap in the literature. Accordingly, a comprehensive review of wetlands, the importance of wetland water-level prediction, and the suitable prediction methods are described in this review. Wetland degradation all over the world has increased due to ongoing urbanization and climate change. Recently, much attention has been paid to the conservation of wetlands due to the awareness of the importance of wetlands in the ecosystem. However, further attention is highly needed. Water level is one of the key elements that support the proper functioning of wetlands. Wetlands have permissible water limits and, therefore, wetland water-level prediction is very important, as water-level measurements are limited in many places. Predictions using mathematical modeling are difficult, as there are many influencing factors, and the relationships between those factors and the water levels are difficult to estimate. The most important factors that affect wetland water levels are precipitation, evaporation, surface inflows, wind speed, soil conditions, etc. Therefore, the selection of a suitable machine-learning technique is very important, as the success of the prediction depends on the data availability and the performance of the algorithm. In this regard, artificial neural networks, support vector machines, random-forest decision trees, etc. were successfully used in wetland water-level prediction all over the world. In particular, artificial neural networks were very effective in wetland water-level prediction, as they behave under nonlinear conditions. This review has enhanced the literature by combining many related works from different parts of the world and presenting a detailed report on what exists in terms of wetland water-level prediction. Any future research can take the lead based on this review to work on solid but conclusive prediction models to predict wetland water levels.

It is well understood that the research on wetland water-level prediction using machine-learning concepts is limited in the literature. Therefore, as suggested by their performance stated in this review, it would be better for planners and authorities to rethink their monitoring processes in worldwide wetlands using machine-learning techniques. However, obtaining real-time climatic data to forecast water levels in wetlands would be a challenging task for most of the wetlands in developing countries. Therefore, it would be better to develop hybrid models that combine machine-learning techniques with hydrological models in future research.

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## List of Abbreviations

| | |
|---|---|
| ANN | Artificial Neural Networks |
| USEPA | United States Environmental Protection Agency |
| HEC-RAS | Hydrologic Engineering Center’s River Analysis System |
| SWAT | The Soil & Water Assessment Tool |
| RBF | Radial Basis Function |
| SVM | Support Vector Machines |
| RF | Random Forests |
| DT | Decision Trees |
| RMSE | root mean squared error |
| $R^2$ | coefficient of determination |

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