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Deep Machine Learning-Based Water Level Prediction Model for Colombo Flood Detention Area

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Abstract: Machine learning has already been proven as a powerful state-of-the-art technique for many non-linear applications, including environmental changes and climate predictions. Wetlands are among some of the most challenging and complex ecosystems for water level predictions. Wetland water level prediction is vital, as wetlands have their own permissible water levels. Exceeding these water levels can cause flooding and other severe environmental damage. On the other hand, the biodiversity of the wetlands is threatened by the sudden fluctuation of water levels. Hence, early prediction of water levels benefits in mitigating most of such environmental damage. However, monitoring and predicting the water levels in wetlands worldwide have been limited owing to various constraints. This study presents the first-ever application of deep machine-learning techniques (deep neural networks) to predict the water level in an urban wetland in Sri Lanka located in its capital. Moreover, for the first time in water level prediction, it investigates two types of relationships: the traditional relationship between water levels and environmental factors, including temperature, humidity, wind speed, and evaporation, and the temporal relationship between daily water levels. Two types of low load artificial neural networks (ANNs) were developed and employed to analyze two relationships which are feed forward neural networks (FFNN) and long short-term memory (LSTM) neural networks, to conduct the comparison on an unbiased common ground. The LSTM has outperformed FFNN and confirmed that the temporal relationship is much more robust in predicting wetland water levels than the traditional relationship. Further, the study identified interesting relationships between prediction accuracy, data volume, ANN type, and degree of information extraction embedded in wetland data. The LSTM neural networks (NN) has achieved substantial performance, including R^2 of 0.8786, mean squared error (*MSE*) of 0.0004, and mean absolute error (*MAE*) of 0.0155 compared to existing studies.

Keywords: artificial neural network (ANN); Colombo flood detention area; machine-learning; feed forward neural network (FFNN); long short-term memory (LSTM); water level prediction; wetlands

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1. Introduction

A wetland is a dynamic system where the land is saturated with water throughout the year, either entirely or partially [1]. Wetlands are characterized as transitional zones between primarily flooded deep water environments and well-drained hills [2]. They are among the most productive ecosystems in the world [3] and play a broad role in environmental, social, and economic aspects. Wetlands act as the kidneys of the landscape, filtering and capturing suspended particles, trapping pollutants such as carbon dioxide and nitrogen, and releasing clean water downstream [4]. They stabilize the global climate, thus acting as carbon sinks [5]. Wetlands accommodate floods, thus reducing flood risk during storms [6,7]. Due to the extensive food chain and the abundant biodiversity, wetlands also have been treated as "nature's supermarkets" [8]. Pollutants such as nitrate in water sources are a significant concern, and wetlands are viable sinks for these pollutants [9–11]. Besides, they enhance water quality, control shoreline erosion, rejuvenate the ecosystem, recharge the groundwater table, facilitate recreation, and aesthetics, etc. [12–14].

Wetlands cover about 6% of the earth's surface [15]. Due to significant land changes due to urbanization, infrastructure development, and agriculture, these ecosystems are under extreme pressure [16]. Wetlands' vulnerability to climate stress has also been confirmed [17]. Therefore, the wetland degradation rate is drastically increasing. According to the 2021 Global wetland outlook report, "Wetland coverage" has been reduced by 35% since 1970 [18]. Since it is one of the most significant ecosystems, it is vital to protect such vulnerable ecosystems. The water level is the crucial parameter that defines the functionality of a wetland [19]. However, most countries still lack a proper mechanism for mapping and monitoring wetland water levels. Hence, water level projection will lead to the protection and proper management of the wetland.

Wetland water levels change in response to variations in water inputs and outputs [20]. Rainfall, surface water inflows, and groundwater inflows are examples of water inputs to wetlands, whereas evaporation, surface water outflows, and seepage are examples of water outputs [21]. Water levels link the wetland's hydrological, meteorological, and geomorphological characteristics to the surroundings [22]. In addition, wetlands are highly vulnerable to changes in the atmosphere. As the air temperature increases, rainfall patterns change and evaporation increases, causing the wetlands to swell [23]. On the other hand, as the temperature rises, relative humidity falls [24,25]. In addition, high wind speed cause more evaporation in the water bodies, lowering their water levels [26].

Altunkaynak [27] used neural networks with backpropagation to forecast Lake Van, Turkey, water levels. They have uncovered that the neural networks give accurate results even though the relationships between the rainfall and consecutive water levels are highly dynamic. They have trained the neural network by having three different arrangements in the input nodes. All three models have produced relatively similar results. One of the significant drawbacks of this study is that they have yet to consider the rest of the meteorological parameters other than the rainfall.

Choi et al. [28] emphasized the significance of predicting wetland water levels while pointing out the difficulties due to the data limitations. They have predicted the water levels in the Upo wetland, South Korea, using several machine-learning techniques, including ANN, decision trees (DT), random forest (RF), and support vector machines (SVM). In addition, researchers have considered the temporal relationship for water level prediction. However, considering only the previous day's water levels will not be adequate for better temporal information extraction through NNs. It is necessary to consider at least 20–30 days of the previous day's water levels for accurate temporal relationship learning.

Dadaser-Celik and Cengiz [29] have predicted the monthly average water levels in Sultan Marshes in Turkey using a multi-layer perceptron-type neural network model. They have investigated the traditional relationship between climate data (rainfall, temperature, evapotranspiration) and hydrological data (groundwater levels, spring flow rate, and the previous month's water levels). Although they have used several input parameters, including the last month's water level, the selected NN type will not support better temporal relationship learning.

Gopakumar and Takara [30] have carried out a study on the investigation of water level fluctuations in the Kerala Vembanad Wetland using ANNs. They have predicted one-day-ahead water levels using rainfall data and the previous day's water levels. The models' results were expressed using several numerical indices, such as the correlation coefficient and root mean square error. Also, they have found that neural networks only predict water levels accurately when there is information on wetland storage conditions. However, this study has not compared both traditional and temporal relationships, which is one of the major concerns. Moreover, it has considered only rainfall among possible environmental factors influencing the wetland water level.

Saha et al. [31] studied wetland water depth and area prediction in the Atreyee River basin using ANN and a non-linear regression model. In this regard, they have used Landsat satellite images of the river basin during pre- and post-monsoon seasons. There could be several drawbacks as they have used image processing data. Prediction accuracy would be limited with a sufficient number of satellite images. Also, images could be noisy because of the clod forming, dust, etc.

Wetland water level measurements are restricted in most countries, especially Sri Lanka. This situation is mainly due to unawareness and lack of attention given by the local authorities. Also, fewer funding allocations for wetland developments have caused improper wetland management and maintenance. Therefore, many wetlands in Sri Lanka have faced severe problems, including insufficient water level measurements. Being the capital of Sri Lanka, wetlands in Colombo city have a significant threat including land degradation. According to recent research, wetland coverage in Colombo city has been reduced by 30% [32]. Wetlands act as flood detention basins. As the wetlands' special coverage is concentrated in Colombo, frequent flash floods are more prone to occur. The lack of water level measurements in Colombo wetlands is a major cause of inadequate flood management in the Colombo region. Also, less attention has been given to water level prediction in Sri Lankan wetlands. The first attempt to simulate the water levels in the Colombo flood detention area was taken recently by Jayathilake et al. [33]. However, it was an initial study to look at the relationship between water levels and climate parameters. Nevertheless, Jayathilake et al. have found the relationship between wetland water levels and climate parameters is highly non-linear [33].

Motivated by the importance of wetlands and monitoring their water level along with the power of deep machine learning techniques (i.e., ANN), this study extends our previous [33] study to investigate and compare traditional relationship and temporal relationships on an unbiased common ground for predicting wetland water level for the first time in this domain using two types of ANNs. In this study, hydrological data and meteorological data have been considered for wetland water level forecasting. In addition, artificial neural network models were developed to simulate the water levels at the Colombo Flood Detention area.

As per the climate parameter prediction literature [34–37], two fundamental types of existing relationships can be considered for predicting the water level of a wetland. The first relationship that was investigated is between the water level and several independent variables (called the traditional relationship hereafter), including daily rainfall, daily evaporation, minimum daily temperature, maximum daily temperature, daily relative humidity during the daytime, daily relative humidity at nighttime, and daily average wind speed. Second, the temporal relationship between daily water levels was investigated. Rainfall was considered the primary factor influencing water balance at the spatial and temporal scales [38]. NNs were selected to model both relationships to maintain a common platform for comparing the two relationships in this study. A simple feed forward neural network (FFNN) was chosen to model the traditional relationship and at the same time, the long short-term memory neural network was used for temporal relationship modeling. Moreover, the authors need to find the simplest NN architectures that require minimum computational processing power and memory requirements with substantial prediction accuracy to run the model on an average computer [39]. It will enable the easy and economical use of the prediction model, especially in remote installations in a country like Sri Lanka.

Primarily, the temporal relationship was never investigated for water level prediction in the past on a comparative basis. The study further investigates the relative accuracy of the relationships, advantages vs disadvantages, and limitations in the two types of predictions. It also examines the available data volume's impact on prediction accuracy. Moreover, the information extraction patterns of each NN will be discussed. The selected

NN architectures are the low-load high, performing NNs selected via detailed model comparison. This is the first-ever application of deep machine-learning techniques for predicting wetland water levels in Sri Lanka.

The remainder of the paper is organized as follows: Section 2 briefly discusses two neural networks considered for water level prediction. Section 3 describes the proposed approach, data sets, and the related techniques used for comparison. Section 4 presents the results with a comprehensive discussion, and Section 5 concludes this work.

2. Application of Neural Networks for Water Level Prediction

Over the past years, artificial neural networks (ANN) have been well developed and employed in many application areas to extract and learn information from various kinds of data [40]. The ANN was inspired by the working principles of the biological brain and the neuron system [41]. Types of ANNs are twofold, based on the connection between neurons as feed forward neural networks and recurrent neural networks (RNN). FFNN does not have a feedback path from the neuron's output to its input, but it does in RNN [42]. Usually, NNs are arranged as interconnected layer architecture [43].

Different types of ANNs have been exercised in various application areas. Selection of the right ANN type is vital for optimal performance. It is significant to consider how structural differences between multiple types of ANNs, such as feed forward neural networks (FFNN), long short-term memory (LSTM) networks, and gated recurrent units (GRU), affect results. Each type of network has its strengths and weaknesses, and the choice of the network depends on the specific task and desired outcomes. For example, FFNN is good at mapping inputs to outputs in a simple, direct way and often functions for tasks such as image classification and regression. LSTM and GRU networks are better suited for tasks involving sequential data, where the current output depends on previous inputs and outputs, as they can maintain long-term dependencies and handle the temporal dynamics of the data. These networks are often used for language modeling and time series prediction tasks.

The first type of relationship selected for the investigation is the traditional one, in which wetland water level as a function of daily rainfall to the catchment, daily evaporation, minimum daily temperature, maximum daily temperature, daily relative humidity at daytime, daily relative humidity at nighttime, and daily average wind speed. Since it is a direct mapping from the aforementioned climate parameters to the water level, the FFNN was selected. To investigate the other relationship, the temporal relationship that exists between daily water levels, the LSTM was selected. The daily water level is a time series signal, and there could exist a temporal relationship between water levels of the nearby days.

2.1. Feed Forward Neural Network (FFNN)

In FFNN, the input information passes through neurons and synaptic weights from input layer neurons to output layer neurons. FFNN uses labeled training data to understand the relationship between the input and output of the given application and accordingly adjust the hyperparameters of the NN. It follows an optimization algorithm named Back Propagation during the training process to converge the model. The prediction error (i.e., the difference between the NN output and the desired output) must be estimated at each epoch. The calculated error propagates backward through the NN, and weights and biases update according to the gradient of error. It uses an error function named Loss Function. The Loss Function can be used to estimate the loss of the NN model so that the weights and biases can be updated to reduce the loss in the next iteration (i.e., epoch). The loss function for the jth neuron at the output layer for nth iteration can be defined as Equation (1).

$$L(n)_{j_\theta} = d_j - y(n)_j \tag{1}$$

where d_j is the desired output, $y(n)_j$ is the NN predicted output, and θ denotes the trainable parameters (i.e., hyperparameters) of the NN. A standard multi-layer FFNN is presented in Figure 1.

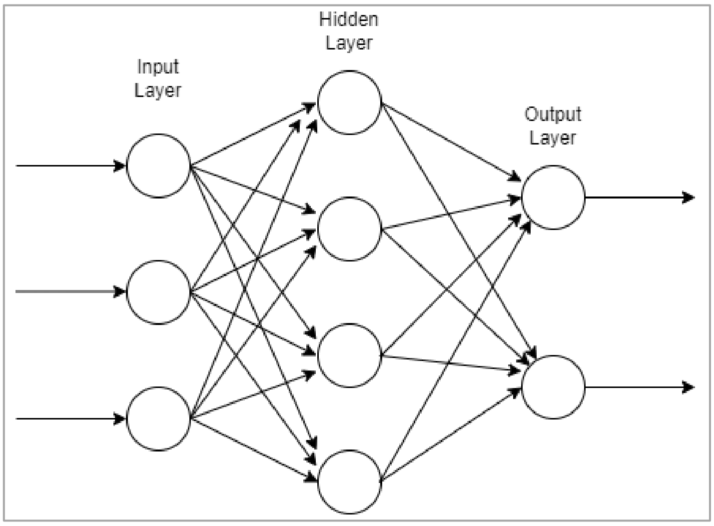

Figure 1. A Multi-layer feed forward neural network.

2.2. *Long Short-Term Memory Neural Networks (LSTM)*

The recurrent neural networks have at least a single feedback connection for their neurons, allowing for retaining previous information (i.e., memory) within the network [42]. However, deep RNNs suffer from vanishing and exploding gradient problems [43]. There are several variants of RNN existing, including LSTM, gated recurrent unit (GRU), and recurrent convolutional neural networks (RCNN) [44]. Among them, LSTM has excellent resistance to gradient problems [45].

The memory capacity and controllability of the LSTM cell have improved by introducing gates to the LSTM cell. Gates supports NN in dealing with the problem of long-term dependencies. It consists of several types of gates within the cell, including forget gate, input gate, and output gate, as illustrated in Figure 2.

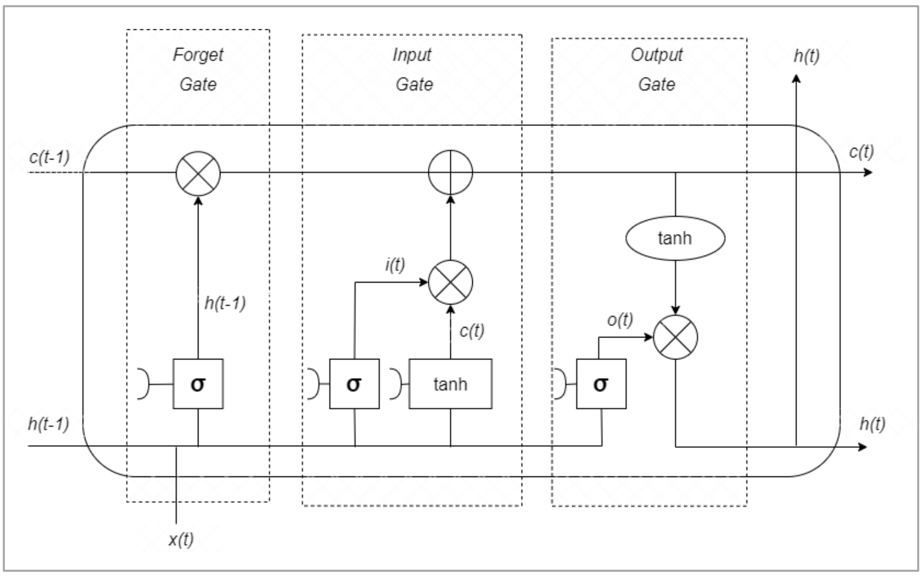

Figure 2. An illustration of LSTM cell.

The mathematical model of an LSTM cell can be presented in the following Equations (2)–(7).

$$\boldsymbol{f_t} = \sigma\ \left(\boldsymbol{W_{fh}h_{t-1}} + \boldsymbol{W_{fx}x_t} + \boldsymbol{b_f}\right) \tag{2}$$

$$\boldsymbol{i_t} = \sigma\ \left(\boldsymbol{W_{ih}h_{t-1}} + \boldsymbol{W_{ix}x_t} + \boldsymbol{b_i}\right) \tag{3}$$

$$\boldsymbol{\widetilde{c}_t} = \boldsymbol{tanh}\ \left(\boldsymbol{W_{\widetilde{c}h}h_{t-1}} + \boldsymbol{W_{\widetilde{c}x}x_t} + \boldsymbol{b_{\widetilde{c}}}\right) \tag{4}$$

$$\boldsymbol{c_t} = \boldsymbol{f_t.c_{t-1}} + \boldsymbol{i_t.\widetilde{c}_t} \tag{5}$$

$$\boldsymbol{o_t} = \sigma\ \left(\boldsymbol{W_{oh}h_{t-1}} + \boldsymbol{W_{ox}x_t} + \boldsymbol{b_o}\right) \tag{6}$$

$$\boldsymbol{h_t} = \boldsymbol{o_t.tanh(c_t)} \tag{7}$$

where $\boldsymbol{c_t}$ denotes the cell state and $\boldsymbol{W_i}$, $\boldsymbol{W_{\widetilde{c}}}$, $\boldsymbol{W_o}$ represent the weights while the "operator is for pointwise multiplication". During the cell state update, the input gate decides what information to store in the cell; the output gate decides what information to send out; and the forget gate decides what information to erase from the cell during the next iteration.

LSTM follows a slightly different algorithm than FFNN, named Back Propagation Through Time to converge the NN since it deals with temporal information related to previous timestamps. In addition, it has much better control of deciding what information to keep and what to remove in the next time stamp. The loss function for LSTM is presented in Equations (8) and (9).

$$\boldsymbol{L_\theta} = \sum_{\boldsymbol{t}} \boldsymbol{L_\theta^{(t)}} \tag{8}$$

$$\boldsymbol{L(\theta)^{(t)}} = \frac{1}{2\boldsymbol{T}} \sum_{\boldsymbol{i}=1}^{\boldsymbol{T}} \left(\boldsymbol{d_j} - \boldsymbol{y(n)_j}\right)^2 \tag{9}$$

where, $\boldsymbol{L_\theta^{(t)}}$ is the loss of time stamp $\boldsymbol{t}$, $\boldsymbol{L_\theta}$ is the cumulative loss, and $\boldsymbol{T}$ is the total duration.

Minimizing the computational load in terms of processing power and memory requirement for real-world water level prediction model implementation is essential, especially for rural and remote implementation. Depending on the NN type, hyperparameter combinations and the depth of the network will decide the computational load. However, in-depth comparisons will enable us to find simple NN models that serve powerful prediction performances compared to more complex NN models. In addition to NN models, genetic programming (GP), and deep GP models are more robust in prediction applications. However, to have a fair comparison between two types of relationships on common ground with low computational loading FFNN and LSTM NNs were selected for the study.

3. Materials and Methods

This section presents the mathematical formulation of the problem, the architecture and hyperparameter selection for the neural networks (NN), input data preparation, input–output mapping topology, and performance indices used for the analysis. This study employed two types of NNs, a simple feed forward NN (FFNN) and a long short-term (LSTM) neural network, for water level prediction purposes.

3.1. Modeling of Feed Forward Neural Network

The FFNNs are used to model the non-linear input-to-output mapping function between independent variables and the dependent variable, which is the water level of the wetland, as presented in Equation (10).

$$WL = F_\theta\left(RF\ , Evap\ , T_{min}, T_{max}, RH_{day}, RH_{night}, WS\ \right) + \delta \tag{10}$$

where WL is the water level of the wetland. RF, $Evap$, T_{min}, T_{max}, RH_{day}, RH_{night}, and WS are daily rainfall to the catchment (in mm), daily evaporation (in mm), minimum daily temperature (in °C), maximum daily temperature (in °C), daily relative humidity at daytime (in %), daily relative humidity at nighttime (in %), and daily average wind speed (in km/h). The F_θ is the mapping function, and δ denotes the prediction error. Hence, the loss function of the FFNN for the given application can be presented as Equation (11), where θ_p represents the trainable parameters of the NN. The architecture of the FFNN used for the prediction is presented in Table 1.

$$L_p = \left(F_\theta \left(RF\ , Evap\ , T_{min}, T_{max}, RH_{day}, RH_{night}, WS\ ,\ \theta_p \right)\ - WL\ \right)^2 \tag{11}$$

Table 1. FNN Network Architecture.

Layer Type	Hyper Parameters (Neurons)	Activation Function
1st Hidden Layer	128	ReLU
2nd Hidden Layer	64	ReLU
Dropout	0.2 Probability	
3rd Hidden Layer	32	ReLU
Dropout	0.2 Probability	
4th Hidden Layer	16	ReLU
Dropout	0.2 Probability	
5th Hidden Layer	8	ReLU
Output Layer	1	Linear

The proposed FFNN accepts seven independent variable readings as inputs mentioned above and tries to predict the water level at the output layer. The input variables may have a varying degree of sensitivity to the water level. Accordingly, the weights and biases of the NN will be adjusted during the training phase. The NNs are very good at mapping such non-linear relationships compared to traditional mathematical models.

3.2. Modeling Long Short-Term Neural Network

The water level of a wetland varies continuously throughout the year. Consequently, the water level of a given day strongly relates to the water levels of previous days. Hence, it can consider a time series signal (TSS). Therefore, the temporal relationship between the daily water levels of a wetland can be considered for future water level prediction. Assuming the temporal information embedded within water level variation during a consecutive thirty days is strong enough for the future forecast, the last thirty-day water levels are used as the input for the next day's water level prediction.

Among the different types of NNs, RNN, LSTM, GRU, and their variants can keep information related to previous input/output data of the NN within it (i.e., maintaining memory). Moreover, LSTM presents greater resistance to the exploding and vanishing gradient, which is one of the critical issues with the RNN family. Considering all facts, LSTM was selected for TSS-based water level prediction. The loss function of LSTM for the given application is presented in Equation (12).

$$L(\theta)^{(t)} = \frac{1}{2T} \sum_{i=1}^{T} \left(F_\theta \left(\boldsymbol{x}^{(t)} \right) - WL^{(t)} \right)^2 \tag{12}$$

where $L_\theta^{(t)}$is the loss of time step t and $\boldsymbol{x}^{(t)}$ is the input vector to the NN. In this application, $T = 30$ and $\boldsymbol{x}^{(t)} = \left[WL_{t-T-1}, WL_{t-(T-1)-1}, \ldots, WL_{t-1} \right]$ where WL is the water level. The architecture of the proposed LSTM network is presented in Table 2.

Table 2. LSTM Neural Network Architecture.

Layer Type	Hyper Parameters	Activation Function
LSTM	96 Units	
Dropout	0.2 Probability	
LSTM	96 Units	
Dropout	0.2 Probability	
LSTM	96 Units	Linear
Dropout	0.2 Probability	
LSTM	96 Units	
Dropout	0.2 Probability	
Dence	1 Neuron	

Both networks were implemented using the Python programming language. Prediction performance was measured using three indicators: R^2 Score, MSE, and MAE. R^2 Score is illustrated in Equation (13). The R^2 Score can be determined as a ratio of the total variation of data points explained by the regression line (sum of squared regression) and the total variation of data points from the mean (also termed as the sum of squares total or total sum of squares).

$$R^2 = \frac{\sum(\hat{y}_i - \overline{y})^2}{\sum(y_i - \overline{y})^2} \tag{13}$$

where $\hat{y}$, and y_i represent the predicted value, mean of the values, and actual value, respectively. Although the R^2 score was used for the analysis, the actual vs predicted water level graphs were also used to demonstrate the prediction performances.

MSE measures the average of the squares of the errors. It can be expressed as in Equation (14). It is an indication of the difference between measured and observed values. MSE is always a positive value. A model performs better when the MSE values are lower. The zero MSE indicates that the model is error-free.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_{i,\ observed} - Y_{i,predicted}\right)^2 \tag{14}$$

MAE is the magnitude of the difference between the predicted value and the observed value and the true value of that relevant observation. It is shown in Equation (15).

$$MAE = \frac{1}{N}\sum_{i=1}^{N} abs(Y_i - \lambda(X_i)) \tag{15}$$

where y_i is the true target value for the test instance x_i, λx_i is the predicted target value for the test instance x_i, and n is the number of test instances.

This study used two different NNs (i.e., FFNN and LAST) to investigate the possible relationships between identified independent variables and water level and the temporal relationship within daily water levels.

For more accurate results, Hyperparameter tuning is essential for NN-based models [46]. This study decided to use manual hyperparameter tuning due to the simplicity of the NN architectures and considering available computational resources. Multiple NN initialization techniques were tested [47], but there was no considerable contribution from the initialization method to reduce the convergence of the prediction model. Finally, random initialization was selected for both NNs since it was marginally better than the others. Several optimizers were tested concerning each model. The Adam optimizer [48] was chosen to compare models due to its unbiased nature. Due to the limited availability of data points, the data was fed as a single batch for model training. However, all data fields were normalized before feeding to the NNs for faster model convergence. Considering the higher possibility of having a non-linear relationship between water level(s) and input climate parameters, the ReLU activation function was selected for FFNN hidden layers.

However, both NNs are used with Liner activation at the output for water level prediction. In addition, the authors trialed several hyperparameter combinations, especially the depth of the NNs, via multiple NN models for both FFNN and LSTM NNs. The prediction accuracy (i.e., R^2, MAE, and MSE) and time taken for a single training epoch were analyzed against the depth of the NN models. After detailed analysis, the proposed two NN architectures were finalized. The time taken per single training epoch was considered as a measure of computational load. Both NN models tested for a different number of training epochs, and 200 epochs was selected considering the optimum accuracy concerning the epoch number.

Uncertainty quantification (UQ) is essential for any prediction model for more accurate and reliable estimation [49–51]. However, UQ can be more time-consuming for NN-based models. It requires substantial amount of data, one of the key-limiting factors for real-world applications like wetland water level predictions. Compared to NN-based models, machine-learning techniques like GP and Deep GP can perform UQ readily without the need for extensive data volume [52].

Proposed models are subjected to both uncertainties, including aleatoric uncertainty and epistemic uncertainties. Within the study, we tried to reduce the impact of epistemic uncertainty by manually finetuning the NN hyperparameters and selecting the most suitable train-test slip after several trials. However, this study had limited data points that led to poor UQ and model generalization.

An Intel® Core i7 processor with 32GB RAM and a Nvidia® GPU with 2GB memory were used for all neural network modelling, training, and testing. The Python programming language was used with Tensorflow® and Keras® (at the backend) for modeling the selected CNN architectures.

4. Case Study

The Colombo flood detention area is located in the western Province of Sri Lanka. As shown in Figure 3, it consists of three wetlands/marshes: Kotte marsh, Kolonnawa marsh, and Heen marsh. The urban landscape surrounds these marshes. The climate in Colombo is tropical monsoon. The average annual temperature ranges from 26.5 °C to 28.5 °C, and it typically receives 2300 mm of precipitation each year. The study area is approximately 1.0–3.0 m above mean sea level. The Metro Colombo Basin covers 105 km^2, and the total wetland coverage is about 20 km^2.

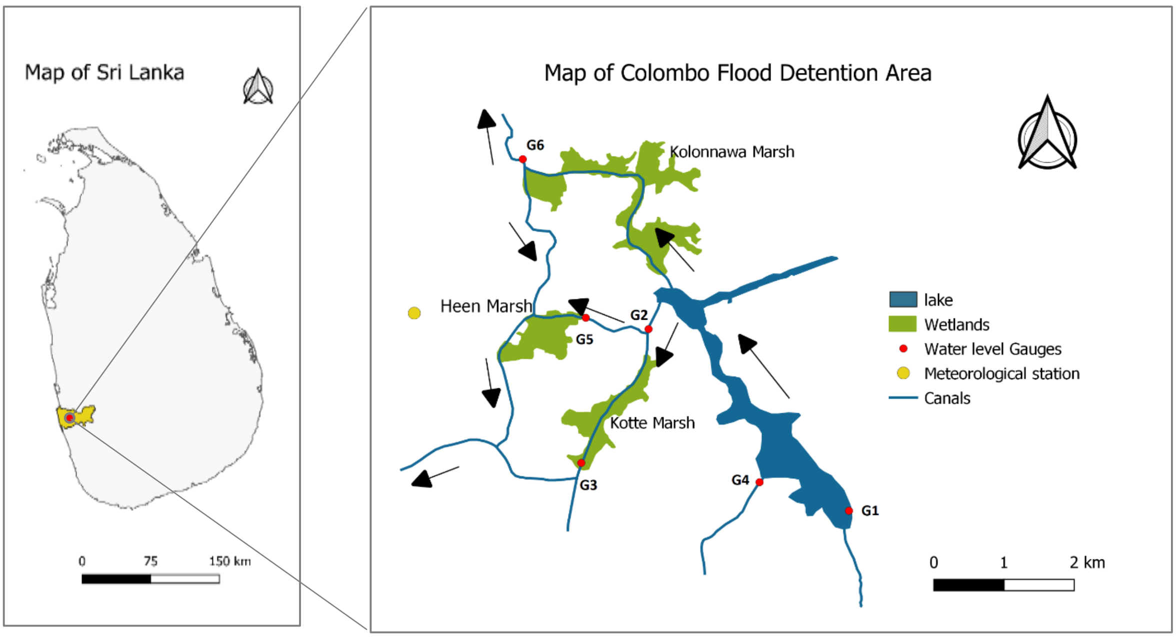

Figure 3. Selected catchment for the study: Colombo flood detention basin.

The capacity of the Colombo flood detention basin has decreased by 30% as a result of urbanization [38]. Hence, flooding is a significant threat to Colombo city. Increased surface runoff brought on by rapid development, declining retention areas, and lack of capacities in wetlands can be identified as the leading causes of flooding. Consequently, Colombo district's flood risk can be reduced by putting strategies in place.

Four water level monitoring stations are located within the basin, Kimbulawala Bridge, Kotte North Canal, Kotte Canal, and Parliament Lake. The data set of each wetland contains daily water levels and the readings of other independent meteorological variables. Wetland water level data were obtained from Sri Lanka Land Development Corporation, while meteorological data were obtained from the Department of Meteorology, Sri Lanka.

The number of data points recorded for each wetland selected for the study differs. Therefore, considering the number of data points, the train-test data split was decided as presented in Table 3.

Table 3. Train-Test Data Split.

Wetland	Total Number of Data Points	Training Data Volume	Testing Data Volume
Kimbulawala Bridge	1887	1500	387
Kotte Canal	1584	1200	384
Kotte North	457	375	82
Parliament Lake	1126	800	326

The range of each variable is substantially different from the range of the others. For example, the temperature range between 20 and 35 °C, the RH value; is between 65 and 95%; the evaporation is between 2 and 3 mm; and the water level is between 0.2 and 0.4 m. This difference in value ranges of each variable will adversely affect the speed of the NN convergence and the time taken to adjust NN hyperparameters. Hence, each variable was normalized to set it between the ranges of 0 and 1, the normalized water level variation, along with the training–testing split presented in Figure 4. In FFNN based prediction model, the water level is used as output, whereas LSTM-based prediction is used as input and output both in the training phase.

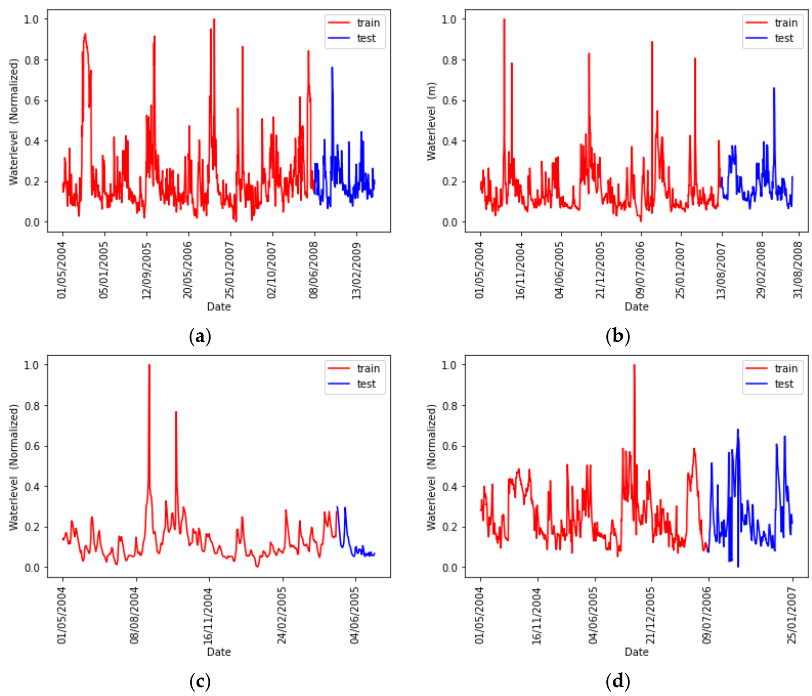

Figure 4. Train–Test data split of (**a**) Kimbulawala, (**b**) Kotte Canal, (**c**) Kotte North, and (**d**) Parliament Lake.

5. Results and Discussion

The R^2 Score, *MSE*, and *MAE* were measured for both FFNN and LSTM network-based models for each wetland water level prediction, and the results are presented in Table 4. The results confirmed that the LSTM had performed better than FFNN in predicting the water levels of the wetlands in all three performance indices considered for the comparison.

Table 4. The water level prediction performances.

Wetland	R^2 Score		*MSE*		*MAE*	
	FFNN	LSTM	FFNN	LSTM	FFNN	LSTM
Kimbulawala Bridge	0.1685	0.8118	0.0212	0.0017	0.0931	0.0249
Kotte Canal	0.2076	0.8786	0.0112	0.0004	0.0668	0.0155
Kotte North	0.1478	0.8345	0.0082	0.0011	0.0548	0.0216
Parliament Lake	0.1530	0.6368	0.0173	0.0069	0.0961	0.0371

The performance of both prediction types (i.e., tradition and temporal) for all wetlands considered for the study is present in Figure 5. It presents similar patterns in both FFNN and LSTM networks' performances against each performance index. Both NNs similarly treated each wetland without any bias. Hence, it confirmed that there is no specific relationship between the water level data of a particular wetland and a given NN type (i.e., LSTM or FFNN). Moreover, a detailed analysis of each wetland's FFNN performance confirmed no difference in the degree of correlation between independent variables selected for investigation with the water level among wetlands.

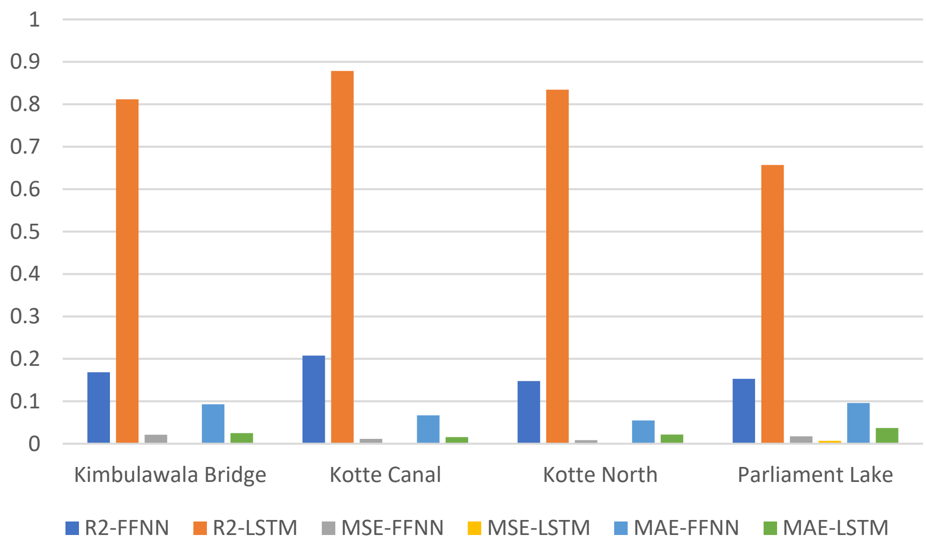

Figure 5. Representation of water level prediction performances.

The performance difference between LSTM- and FFNN-based models for all wetlands is substantial. The higher performance of LSTM over FFNN concludes that the temporal relationship between the daily water level is much stronger than that between the identified independent variables and water level. However, the number of data points may be inadequate to learn the composite relationship between the seven independent variables and the water level in the FFNN approach. The highest number of data points used for the investigation is 1887 from the Kimbulawala Bridge wetland. As per the thumb rule, it is required to have at least a few 100,000 data points to learn the relationship, especially for seven input variables, successfully. Hence, increasing the volume of training data can improve the prediction performance of FFNN.

The NN prediction performances (R^2) were further analyzed against the training data volume of the respective wetland. In order to make a better graphical comparison, normalized values of each field are calculated as presented in Table 5, and Figure 6 illustrates the performance variation viz. training data volume. The normalization will not affect the performance comparison since it is only used to analyze the relative shape of performance pattern variation.

Table 5. Normalized performances and training data volume.

Wetland	Training Data Volume	R^2 Value of FFNN	R^2 Value of LSTM	Normalized Training Data Volume	Normalized R^2 Value of FFNN	Normalized R^2 Value of LSTM
Kimbulawala Bridge	1500	0.1685	0.7917	0.3870	0.2572	0.2520
Kotte Canal	1200	0.2076	0.8786	0.3096	0.3168	0.2796
Kotte North	800	0.126	0.8345	0.2064	0.1923	0.2656
Parliament Lake	375	0.153	0.6368	0.0967	0.2335	0.2026

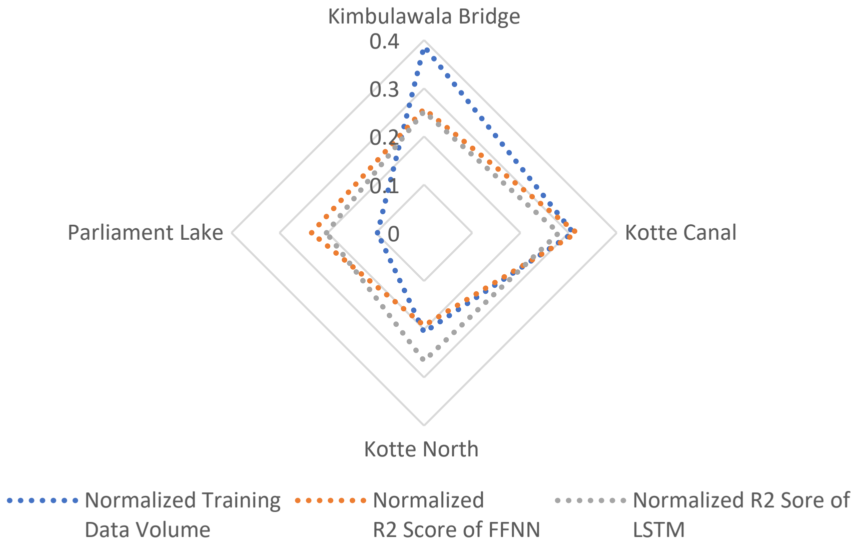

Figure 6. Normalized prediction performances (R^2 Score) and training data volume analysis.

As per the graphical illustration of Figure 6, both FFNN and LSTM prediction models followed a similar pattern (only the shape of variation but not performance values) in the normalized performance. Hence, it confirmed both NNs endeavored to discover the hidden relationships (i.e., two types of relationships) for water level prediction. Moreover, although two kinds of relationships considered for the study (i.e., temporal and traditional) have provided a different level of performance, both have a similar degree of information within all wetland data. Therefore, both NNs extracted two types of relationship information from each wetland data in an almost similar ratio. This is confirmed by having normalized performance patterns with the same shape. However, as per Figure 5, it could not find a strong relationship between the amount of training data and prediction accuracy between wetlands. Hence, it confirmed the degree of relationship information embedded in the given wetland data is much more important than the available volume of data for accurate water level prediction.

Since LSTM-based prediction provided a higher performance, LSTM was selected for further analysis. The comparison between the actual and predicted water levels by the LSTM network for each wetland is presented in Figure 7. Except for a few days in the Parliament Lake wetland, for all other wetlands, the LSTM model was able to provide greater prediction accuracy. Although, in some applications, the R^2 score failed to represent a direct comparison performance of actual vs. predicted but represents a correlation. However, in this application, the comparison graphs confirmed that R^2 was able to directly compare actual vs predicted water levels together with other performance indices that *MSE* and *MAE* selected for the analysis.

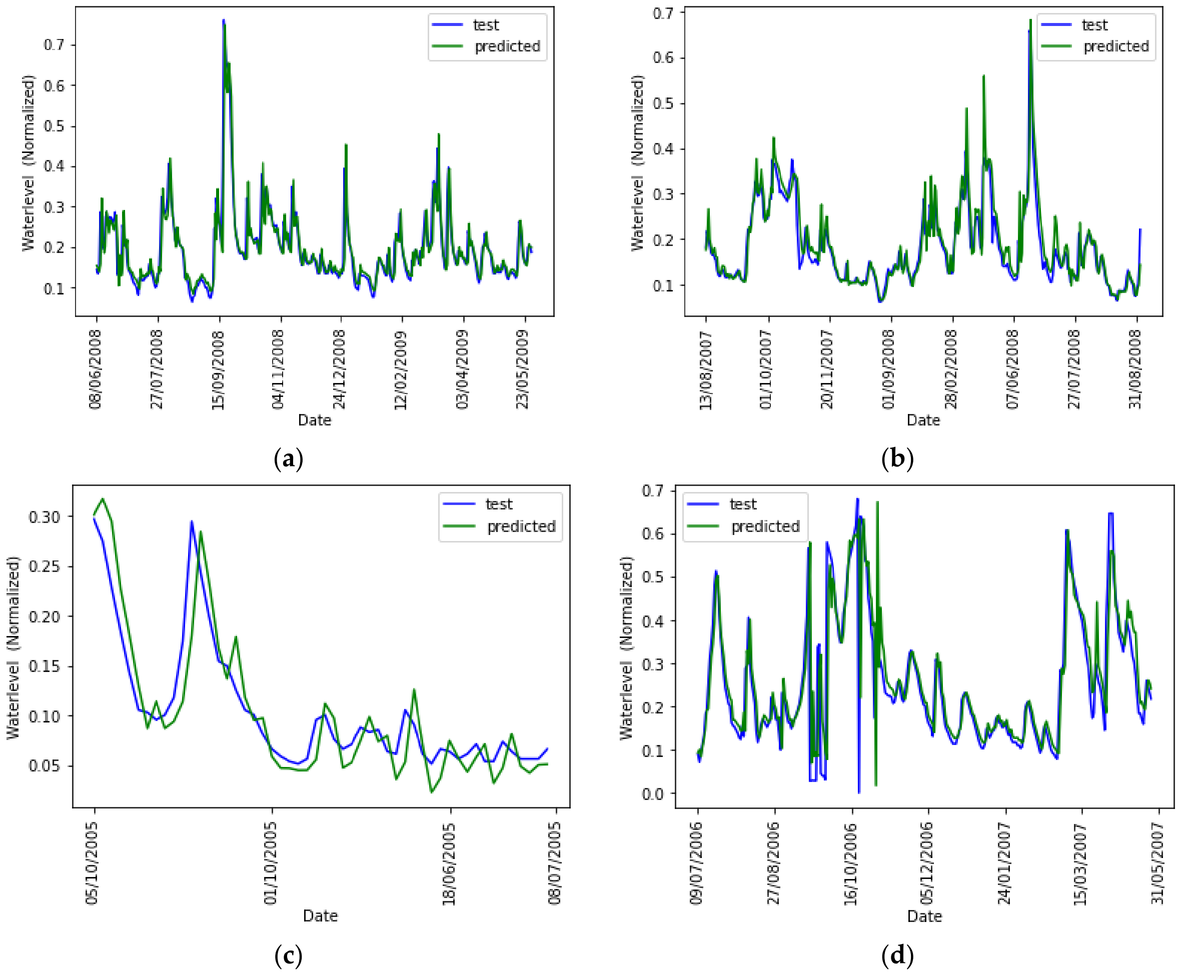

Figure 7. Actual vs. predicted water level comparison for LSTM-based model of (**a**) Kimbulawala, (**b**) Kotte Canal, (**c**) Kotte North, and (**d**) Parliament Lake.

A comparison of actual vs predicted water levels in the graphs for all wetlands showed that the LSTM model could accurately predict average and extreme values (i.e., peaks and valleys). It confirms the greater generalization capability of the LSTM-based prediction model. A few variations can be found in the graphs, especially for the Kotte North wetland water level prediction. As stated, the relationship between water levels in a wetland is highly non-linear and complex. Hence, the achieved prediction performance of LSTM is outstanding. These results indirectly confirm the robustness of the prediction model against UQ, especially in extreme values (i.e., peaks and valleys) of water levels.

Further, the loss curves of the LSTM network during the training period were analyzed and presented in Figure 8. It will provide insights into NN learning behavior, capability, and speed. As per the loss curves, Kotte Canal showed the best convergence behavior, which was reflected in the results of the R^2 score comparison in Table 6. It concludes that the amount of embedded relationship information within the data set is much more substantial than the training data volume in water level prediction.

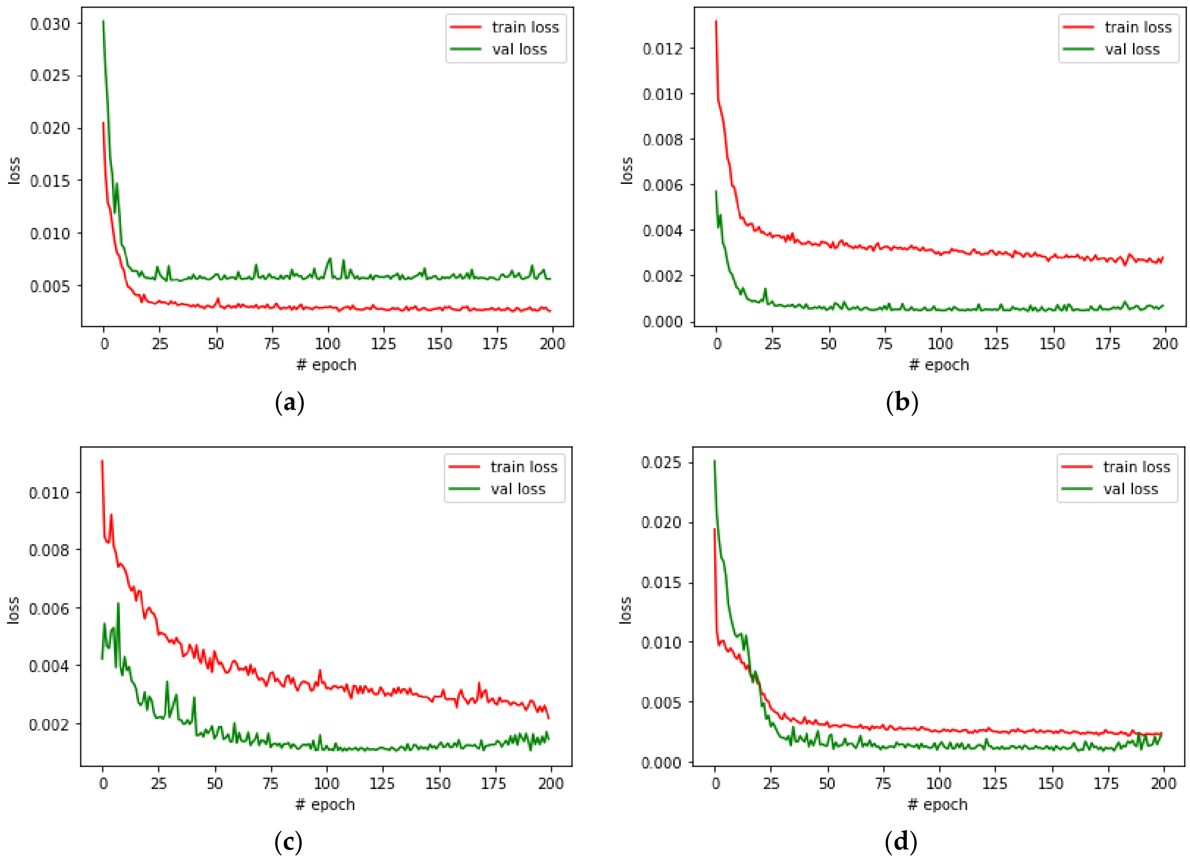

Figure 8. Loss curves of LSTM-based model for (**a**) Kimbulawala, (**b**) Kotte Canal, (**c**) Kotte North, and (**d**) Parliament Lake.

Table 6. Comparison of perdition performance of the LSTM model with existing studies.

Disaggregation Studies	R^2 Score	*MSE*	*MAE*
Vaheddoost, Aksoy, & Abghari, 2016 [53]	0.989	-	-
Young, Liu, & Hsieh, 2015 [54]	0.985	-	1.27
Assem et al., 2017 [55]	0.853	-	0.039
Daliakopoulos, Coulibaly, & Tsanis, 2005 [56]	0.985	-	-
Current study	0.8786	0.0004	0.0155

The performance of the proposed model is compared with the performance of the existing studies, as presented in Table 6, although the study is for relationship comparison. Table 6 contains two wetland water level predictions: one urban water flow prediction and one groundwater level prediction performance. All the listed studies used a large volume of training data compared with the current study. In contrast, the proposed LSTM model has achieved substantial results using limited training data.

One of the critical limitations of the study is the inadequate amount of data for the analysis. For effective model development, it is required to have at least a few 100,000 data points per wetland. In addition, it was assumed that the independent variable readings did not deviate considerably during that day from the record measurement. However, the study showcases the importance of closely monitoring wetland data in Sri Lanka for sustainable water resources management. It is well understood that traditional data monitoring process can be cost consuming; however, water level measuring and weather sensors can be effectively used for long-term data recording without much human intervention.

6. Conclusions

Extant literature is limited to considering only the traditional relationship between environmental parameters and wetland water level for future water level predictions. For future projections, this study presents a novel concept using a temporal relationship between daily wetland water levels. Moreover, both traditional and temporal relationships were modeled using two types of ANN, and prediction performance was analyzed in detail. Several NN architectures were compared within the study, and lightweight, high-performing NN models for LSTM and FFNN were selected.

The results confirmed that the temporal relationship within daily wetland water levels is much more robust in predicting future water levels than using the traditional relationship between environmental parameters and water level. The detailed analysis found that the degree of embedded relationship information within the wetland data is more critical than the volume of training data regarding water level prediction. Moreover, the normalized performance graph comparison presented that although the performance level substantially differs between FFNN and LSTM models, the prediction accuracy pattern between wetlands is similar. Hence, two prediction models learned two different relationships from wetland data in almost the same ratio from each wetland. The actual vs predicted water level graphs reconfirm the performance measured using the R^2 Score, MSE, and MAE. The model can predict extreme cases like very high and low water levels, which is essential in the said application area. It also reconfirmed the greater generalization capability of the proposed LSTM model and its robustness against the uncertainties.

However, ANN models are subjected to considerable deviation in predicting results out of the training data range. Hence it is required to accommodate a wider range of data for model training. Manual hyperparameter training is an exhaustive effort, and it is necessary to have expert knowledge compared to automatic hyperparameter tuning models. Compared to other techniques like GP that can perform UQ readily, it is comparatively difficult to accommodate uncertainty quantification for the ANN-based models due to limited training data and extensive time consumption.

Future studies can investigate and select the most influenceable input parameters (i.e., variables) for water level predictions than using all seven identified input variables. Moreover, immediate effect analysis for water level variation from some selected input variables can be analyzed as an extended study. Finally, the comparative study will be extended to a comprehensive analysis of soft computing methods, including ANNs, GP, and other ML techniques for wetland water level prediction.

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