Vol. 14, No. 5 (2025): 1638 - 1649 https://doi.org/10.23960/jtepl.v14i5.1638-1649

JURNAL TEKNIK PERTANIAN LAMPUNG

ISSN 2302-559X (print) / 2549-0818 (online)
Journal homepage : https://jurnal.fp.unila.ac.id/index.php/JTP

Application of Extreme Learning Machine (ELM) for Water Level Prediction in Krueng Peusangan River Basin (2014–2023)

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Article History:

Received : 14 April 2025
Revised : 09 June 2025
Accepted : 27 June 2025

Keywords:

Artificial neural networks,
Extreme learning machine,
Flood mitigation,
Prediction,
River flow.

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ABSTRACT

The Krueng Peusangan Watershed in Aceh Province is highly vulnerable to flooding, with 20.39% of its area classified as flood-prone, particularly in Bireuen Regency. This study aims to develop a water level prediction model using the Extreme Learning Machine (ELM), a type of Artificial Neural Network known for its computational efficiency and ability to handle uncertainty in hydrological data. The model was trained using water level data from the Krueng Peusangan River from January 2014 to June 2023. The results show a Mean Squared Error (MSE) of 0.063, indicating high predictive accuracy. Compared to conventional methods, ELM delivers faster computation and better precision. This research contributes to the development of data-driven flood early warning systems, supports adaptive and sustainable water resource management, and offers potential for replication in other watersheds with similar characteristics. Furthermore, the model provides a scientific basis for formulating disaster risk reduction policies leveraging artificial intelligence technologies. The promising accuracy of ELM supports its potential integration into real-time flood early warning systems and long-term adaptive water resource management in vulnerable river basins.

1. INTRODUCTION

Global climate change triggered by global warming has caused significant impacts worldwide, including the increased frequency and intensity of extreme rainfall events (Syafitri & Harahap, 2023; Ramli *et al*., 2019a). This phenomenon has led to frequent floods in many regions, further threatening human lives and the economy. Flooding can damage critical infrastructure, homes, and agricultural land, which is the primary source of livelihood for many communities. The effects of this climate change are becoming increasingly alarming, as they threaten food security, health, and the well-being of people in various areas. Therefore, this phenomenon has become a major concern for many parties, especially in regions vulnerable to natural disasters, including floods (Rahmi *et al*., 2024; Zalmita *et al*., 2021).

One of the areas affected by climate change is the Krueng Peusangan River basin located in Aceh. This river plays an important role in supporting agricultural, fisheries, and domestic water needs for the local community. Historically, it has been the main water source for agricultural activities and also serves as a transportation route for fishery products (Ferijal *et al*., 2016). However, in recent years, the region has experienced an increase in the frequency of floods, causing significant damage (Tyagi *et al*., 2014; Yulida *et al*., 2022). The damage includes the destruction of infrastructure, the collapse of residents' homes, and the flooding of agricultural land, which directly impacts the local economy, which heavily relies on these sectors.

The Krueng Peusangan river basin is highly vulnerable to flooding. This is due to various biophysical factors that affect the river's capacity to store and flow water effectively. These factors include the area's low-lying topography, uncontrolled land use, and increasingly unpredictable rainfall patterns (Rahmi *et al*., 2024; Ramli *et al*., 2021; Achmad *et al*., 2024; Ramli *et al*., 2019b). In addition to the more frequent extreme weather events caused by climate change, poorly planned land use changes also exacerbate the river's ability to manage water flow. The conversion of farm land into settlements or industrial areas, as well as deforestation, leads to a reduction in the soil's ability to absorb rain water, contributing to the increased volume of water flowing into the river and worsening the potential for flooding.

In facing this situation, it is crucial to have an accurate method for predicting water flow, so that the potential for flooding can be estimated and mitigation efforts can be carried out more effectively. Accurate water flow predictions can help local governments and communities prepare preventive measures before flooding occurs. One method widely used in modern hydrology is the application of machine learning techniques, one of which is Extreme Learning Machine (ELM) (Dewi *et al*., 2018). ELM is a relatively new machine learning method that has rapidly developed in recent years. This method is used to improve accuracy in predicting water flow, especially compared to traditional methods such as linear regression or more complex physical hydrological models (Rachmawardani *et al*., 2022).

ELM works differently compared to traditional artificial neural networks. In ELM, the weights in the hidden layer of the neural network are determined randomly, which makes the training process much faster and more efficient (Rochman *et al*., 2018). The main advantage of ELM is its ability to handle data with high uncertainty and significant variation, which is often encountered in hydrological data. By using ELM, the training process can be completed in a shorter time, while still producing a model with high accuracy. Several studies have shown that ELM can provide more accurate predictions in forecasting monthly river flow, compared to other methods such as linear regression or ARIMA (AutoRegressive Integrated Moving Average) models (Rochman *et al*., 2018; Ridwan *et al*., 2021).

The use of ELM in this study is highly relevant, considering that historical water level data in the Krueng Peusangan river basin is already available and can be used for more in-depth analysis (Padhila *et al*., 2022). Although this historical data exists, accurate and relevant predictions require more advanced and efficient analytical techniques such as ELM. By utilizing ELM, water flow predictions can be made more accurately and timely, which will be extremely useful for water resource managers and other relevant parties in planning more effective flood mitigation strategies (Sandiwarno, 2024).

In addition, the combination of ELM's efficient and accurate potential with a comprehensive data-driven flood management strategy is expected to make a significant contribution to reducing the impact of floods on local communities. In the face of climate change, which has led to an increase in extreme rainfall, this prediction-based approach will be extremely helpful in designing more appropriate and timely mitigation policies and actions. To date, no studies have applied ELM in the Krueng Peusangan Watershed, making this research a novel and relevant contribution both scientifically and practically. Therefore, this study aims to develop a water level prediction model that not only enhances the accuracy of predictions but also provides a solid foundation for policymakers to design more effective flood mitigation strategies in the Krueng Peusangan river basin. With the right measures in place, the negative impacts of climate change, particularly flooding, can be minimized, and the well-being of the community can be safeguarded. The expected benefit of this research is to support the development of adaptive and data-driven flood management policies that can be applied not only in the Krueng Peusangan river basin but also as a reference for other regions facing similar hydrological challenges.

2. METHOD

The data used in this study was secondary data obtained from the River Basin Management Office (BWS), which provided information on the water level of the Krueng Peusangan River (Figure 1). The Krueng Peusangan Watershed, located in Aceh Province, is highly vulnerable to flooding, with 20.39% of its area classified as flood-prone, particularly in Bireuen Regency. The data spans a considerable period, from January 2014 to June 2023. The water level data collected during this period is crucial for analyzing the patterns of water level changes in the Krueng Peusangan River, which will serve as the basis for the prediction model. By utilizing this secondary data, the study can leverage previously recorded information, enabling a more in-depth and accurate analysis of the factors affecting

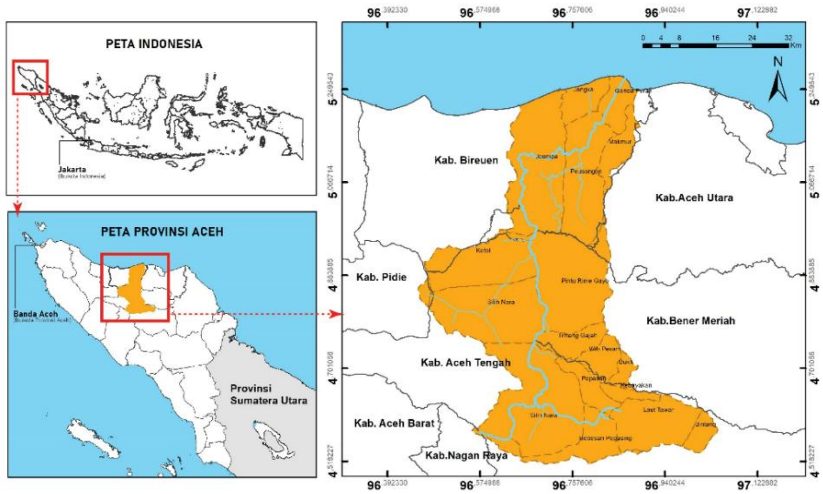


Figure 1. Research Location

water level changes in the watershed area. The relationship is represented by the function $Y = f(X_1, X_2, X_3)$ shows that X1 represents the water level data in the morning, X_2 represents the water level data in the afternoon, X_3 represents the water level data in the evening, and Y represents the average of all water levels.

2.1 Extreme Learning Machine (ELM)

In general, the artificial neural network model that applies Extreme Learning Machine (ELM) as its learning method (Figure 2), as proposed by (Huang *et al*., 2004). This figure 3 provides a basic structural overview of how the ELM framework is implemented within the network. The calculation process in the ELM method is divided into two main stages: the training process and the testing process.

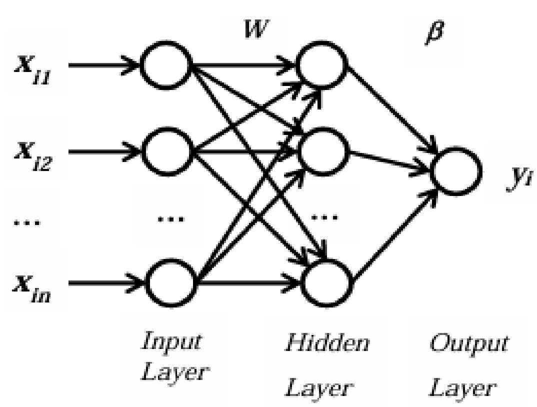


Figure 2. The structure of an Extreme Learning Machine (ELM)

2.1.1 Training Process

Figure 2 illustrates the ELM-based neural network model proposed by Huang *et al*. (2006). The training process stages were as follows:

1. Randomly initialize input weights and biases in the range -1 to 1.
2. Compute hidden layer outputs using a nonlinear activation function (Eq. 1).

$$H_{i,j} = \left(\sum_{k=1}^{n} x_{ik} \,.\, w_{jk}\right) + b_j \tag{1}$$

where $H_{i,j}$ is matrix element H in row i column j, i = [1,2, …, N], where N is the amount of data, j = [1,2, …, $\widetilde{N}$], k is number of input neurons, w_{jk} is the weight connecting the input neuron to the hidden neuron i, n is number of hidden layer neurons, b_j is bias of the hidden neuron, and x_{ik} is input data vector.

3. The hidden layer output (H) was processed using a sigmoid activation function, $f(x)$, to map values between 0 and 1 (Eq. 2).

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

4. The transposed hidden layer output (after activation) is used to compute neural network weights in ELM.
5. Calculating the Moore-Penrose Generalized Inverse Matrix (H^+), as shown in (Eq. 3).

$$H^+ = (H^T H)^{-1} H^T \tag{3}$$

where H is hidden layer matrix with the activation function

6. Output weights matrix (β) are computed from the hidden to output layer for accurate predictions (Eq. 4).

$$\beta = H^+ T \tag{4}$$

where T is target matrix

2.1.2. Testing Process

The steps in the testing process are as follows:

1. Apply trained weights and biases to new inputs.
2. Compute hidden layer output
3. Next, calculate the output layer result (y), which is the prediction outcome, as shown in (Eq. 5).

$$y = H\beta \tag{5}$$

2.1.3. Data Normalization

To keep outputs within range, ELM applies Min-Max normalization to scale inputs between 0 and 1 (Eq. 6).

$$x' = \frac{x - min}{max - min} \tag{6}$$

where x'= normalized data value, x= data value before normalization, *min* = minimum value in the dataset, *max* = maximum value in the dataset.

2.1.4. Data Denormalization

To interpret results in real scale, denormalization is applied to reverse normalization (Eq. 7).

$$x = x'(max - \min) + min \tag{7}$$

where x' is data value before denormalization, and x is data value after denormalization

2.1.5. Mean Square Error (MSE)

Mean Square Error (MSE) evaluates ELM performance by comparing predicted and actual outputs (Eq. 8).

$$MSE = \frac{\sum_{i=1}^{n} e_i^2}{n} = \frac{\sum_{i=1}^{n} (y_i - t_i)^2}{n} \tag{8}$$

where n = number of data, e = error, y_i = output value (prediction), and t_i = actual value

2.1.6. Relative Root Mean Square Error (RRMSE)

Relative Root Mean Mean Square Error (RRMSE) evaluates ELM performance by comparing predicted and actual outputs (Eq. 8).

$$RMSE = \sqrt{MSE} \tag{9}$$

$$RRMSE = \frac{RMSE}{\bar{y}} \times 100\% \tag{10}$$

where $RRMSE$ is the square root of the prediction error variance, and $\bar{y}$ is the average of the actual values

All ELM computations were implemented in MATLAB R2023a, which provides efficient matrix operations and visualization tools. The training and testing datasets were processed using built-in functions, and the ELM algorithm was coded manually for flexibility in model architecture and evaluation.

2.2 Water Level Prediction Model for Krueng Peusangan

The prediction model in ELM is a mathematical representation of the relationship between input data and output that is learned by the ELM (Huang *et al*., 2006). This model is used to map input data (X) to the predicted output (Y). based on previous training with the target data (T). In this study, the best ELM model produced is:

The output matrix of the hidden layer is represented as H_i.

$$H_i = b_i + \sum_{j=1}^{11}(x_j \times w_{i,j}) \tag{11}$$

$$H_1 = b_1 + \sum_{j=1}^{11}(x_j \times w_{1,j})$$

$$H_1 = b_1 + \left[(x_1 \times w_{1,1}) + (x_2 \times w_{1,2}) + (x_3 \times w_{1,3}) + \cdots + (x_{11} \times w_{1,11})\right]$$

$$H_2 = b_2 + \left[(x_1 \times w_{2,1}) + (x_2 \times w_{2,2}) + (x_3 \times w_{2,3}) + \cdots + (x_{11} \times w_{2,11})\right]$$

$$H_3 = b_3 + \left[(x_1 \times w_{3,1}) + (x_2 \times w_{3,2}) + (x_3 \times w_{3,3}) + \cdots + (x_{11} \times w_{3,11})\right]$$

$$\vdots$$

$$H_9 = b_9 + \left[(x_1 \times w_{9,1}) + (x_2 \times w_{9,2}) + (x_3 \times w_{9,3}) + \cdots + (x_{11} \times w_{9,11})\right]$$

The output matrix of the hidden layer with an activation function= $G_i = g(H_i)$

$$G_i = g(H_i) = \frac{1}{1+e^{(-H_i)}} \tag{12}$$

$$G_1 = g(H_1) = \frac{1}{1+e^{(-H_1)}}$$

$$G_2 = g(H_2) = \frac{1}{1+e^{(-H_2)}}$$

$$G_3 = g(H_3) = \frac{1}{1+e^{(-H_3)}}$$

$$\vdots$$

$$G_{11} = g(H_9) = \frac{1}{1+e^{(-H_9)}}$$

The prediction results $= Y$

$$Y = \sum_{i=1}^{9}(\beta_i \times G_i) \tag{13}$$

$$Y = [(\beta_1 \times G_1) + (\beta_2 \times G_2) + (\beta_3 \times G_3) + \cdots + (\beta_9 \times G_9)]$$

Therefore, if Y is expanded, it will become :

$$Y = \sum_{i=1}^{9}\left[\beta_i \times g\left(b_i + \sum_{j=1}^{11}(x_j \times w_{i,j})\right)\right] \tag{14}$$

where Y is the predicted output, β_i is output weight, w_{ik} is the weight that connects the input neuron to the hidden neuron-i, n is the number of neurons in the hidden layer, b_j is the bias in the hidden neuron, $x_j$is the input data vector.

3. RESULTS AND DISCUSSION

3.1 Determining Input Neuron and Neuron Layer

The water level data used consists of 2.755 data points. The data is then split into 2,204 for training data and 551 for testing data, with a training-to-testing data ratio of 80%:20%. The number of input layers is set to 11, with 9 hidden layers. Next, the prediction calculation is carried out using the best input layer and hidden layer. To provide a clearer representation of the data pattern and distribution, a scatter plot of the water level data is presented in Figure 3.

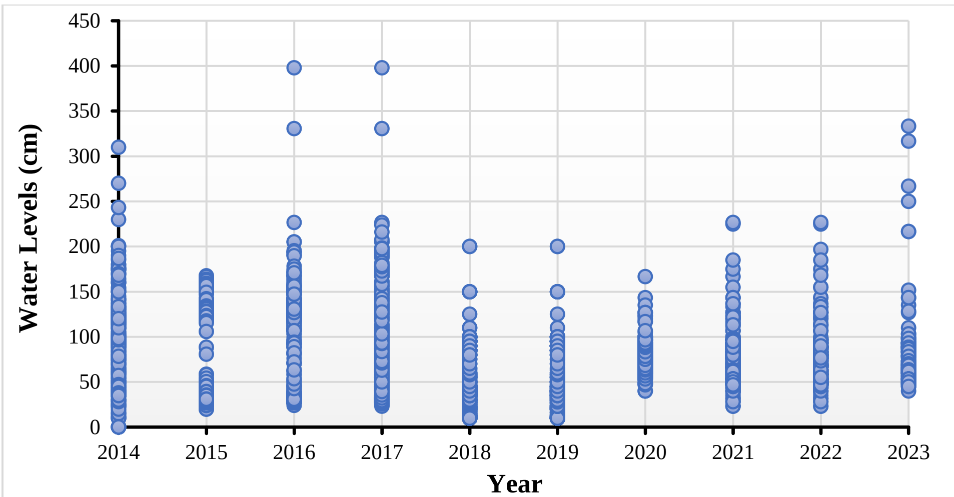


Figure 3. Water level data of the Krueng Peusangan River during 2014-2023

Table 1. Comparison of MSE values for 11 input layer neurons with 1, 5, 7, 9, and 11 hidden neurons

	Hidden Neurons with 11 Input Layer Neurons				
	1	**5**	**7**	**9**	**11**
1	4.942	0.585	0.453	0.072	0.749
2	2.433	0.846	0.547	0.012	0.688
3	3.687	0.790	0.951	0.007	0.627
4	3.463	0.832	0.917	0.044	0.851
5	3.330	0.498	0.578	0.019	0.530
6	2.882	0.951	1.004	0.028	0.646
7	3.626	0.742	0.675	0.010	0.544
8	2.882	0.873	0.817	0.260	0.606
9	2.884	0.634	0.798	0.047	0.679
10	3.592	0.610	0.687	0.126	0.559
Average	3.372	0.736	0.743	0.063	0.648

At this stage, testing is conducted on the number of input neurons and neurons in the layer being used. The goal is to achieve better prediction results. Determining the number of neurons in the input and hidden layers is crucial in the Extreme Learning Machine (ELM) method, as it directly affects the model's performance in making predictions. The number of neurons in the hidden layer is a key parameter that influences the model’s ability to generalize. Too few neurons can lead to underfitting, where the model is not complex enough to capture the data patterns. Too many neurons can result in overfitting, where the model becomes too complex and fits the noise in the data, reducing its generalization ability. Therefore, in this study, the number of neurons in the input layer tested was 11, while the number of neurons in the hidden layer tested was 1, 5, 7, 9, and 11.

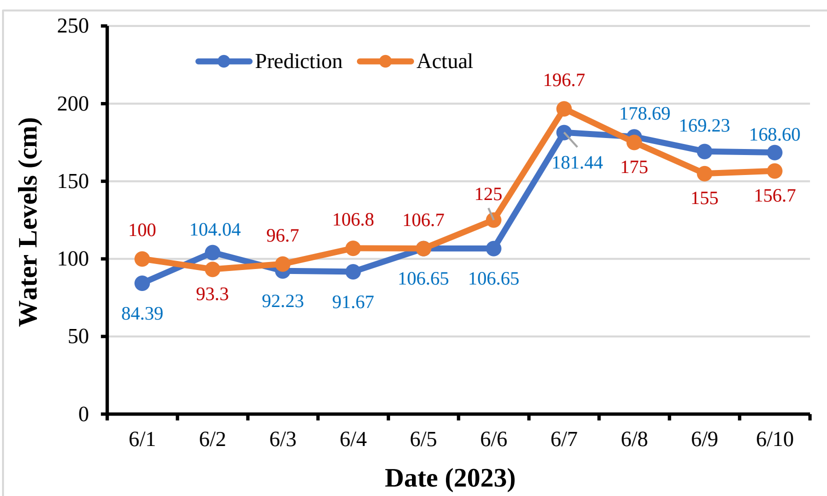
Table 1 shows a comparison of the testing results for the number of neurons in the input layer (11 neurons) and hidden layer (1, 5, 7, 9, and 11 neurons) as follows. With various numbers of neurons in the hidden layer specifically

1, 5, 7, 9, and 11 units the table aims to demonstrate how changes in the number of hidden neurons affect the model's performance in predicting water level. This comparison allows for the identification of the most effective neuron configuration in producing an optimal model, as well as its impact on the prediction accuracy of the artificial neural network employed in this study. As shown in the Table 1, the lowest Mean Squared Error (MSE) is achieved when using 9 hidden neurons, with an MSE value of 0.063. Thus, the model with 9 hidden neurons is considered optimal, as it is capable of capturing daily variations without overfitting. Therefore, based on the tables above, it can be concluded that the smallest average MSE value is found with the 11th input layer and 9 hidden neurons, with an MSE value of 0.063. Thus, to predict the water level in the Peusangan River Basin (DAS Krueng Peusangan), the 11th input layer and the 9th hidden layer neurons are used.

3.1. Comparison of Predicted and Actual Water Level Values

The comparison results between predicted and actual values water level data are used to evaluate the performance of the applied model. The analysis is conducted by calculating evaluation metrics such as Mean Squared Error (MSE) to measure the model's accuracy level. Additionally, this comparison helps determine whether the model experiences overfitting or underfitting and assists in refining the model to produce more accurate predictions (Figure 4).

The ELM method is very relevant in hydrological prediction and flood management. (Xu *et al*., 2023) Based on the comparison of predicted and actual values over the next 10 days, it is evident that the prediction model has a fairly good accuracy level with varying errors. On certain days, such as 6/5/2023 (0.04), the model produces results very close to the actual values, indicating accurate predictions. The graph shows a comparison between predicted values (blue line) and actual values (red line) over the next 10 days based on testing data. In general, the prediction pattern follows the trend of actual values, although there are some differences at certain points. On specific days, such as 6/4/2023 and 6/5/2023, the predicted values closely match the actual values, indicating high model accuracy. This graph helps evaluate the performance of the prediction model and determine steps to improve accuracy.



Date	Absolute Error (cm)
6/1/2023	15.61
6/2/2023	10.74
6/3/2023	4.47
6/4/2023	15.13
6/5/2023	0.05
6/6/2023	18.35
6/7/2023	15.25
6/8/2023	3.69
6/9/2023	14.22
6/10/2023	11.89

Figure 4. Comparison of prediction and actual results for the next 10 days with absolute errors in the right

3.2 Prediction Results Based on MSE Values Using Training and Testing

The water level prediction testing based on training and testing data with an 80%:20% split was conducted using Excel 2017 and Matlab. The prediction results for the next 50 days, starting in July 2023, can be seen in Figure 5. The lowest predicted value occurred on Sunday, July 2, with a water level of 50.78 cm, while the highest predicted value was recorded on Friday in August, reaching 61.39 cm. The test results indicate that during the first seven weeks, the water level remained within the normal category without any significant peaks. The predicted water level results are illustrated in Figure 5. Thus, the lowest predicted value occurred on Saturday, July 1st, with a water level of

47.04 cm, while the highest predicted value was recorded on Friday in August, reaching 60.49 cm. These test results indicate that during the first seven weeks, the water level remained within a normal range, with no significant increases in water level.

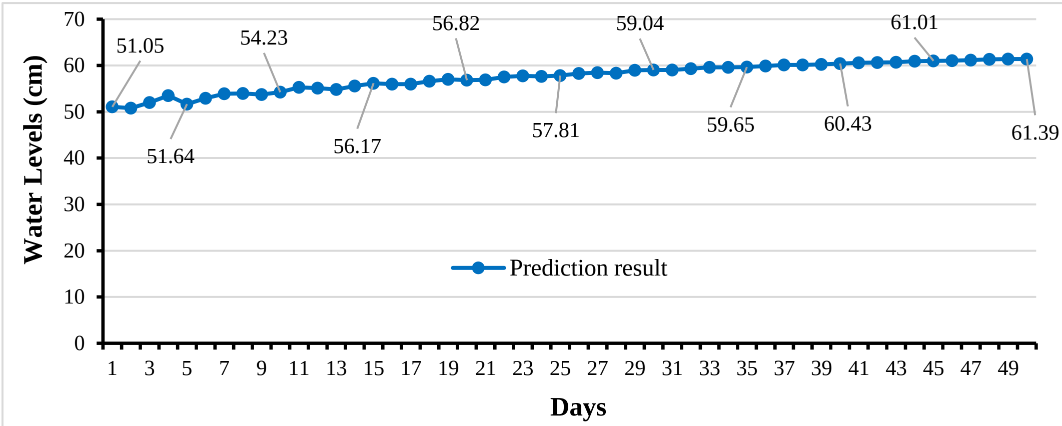


Figure 5. Predicted water level for the next 50 days

The increase in water levels over the seven weeks could be influenced by various factors, such as rain-fall patterns, hydrological conditions, or human activities in the surrounding area. However, the water level remained within the "normal" range, meaning it has not yet reached levels that indicate a high-risk or flood situation. In hydrological terms, a high water level occurs when the water surpasses the capacity of the channel or storage reservoir. A water level ranging from 50.78 cm to 61.39 cm indicates that the storage system is still capable of holding the water without high risk. This suggests that the first seven-week observation period remained within a safe hydrological limit.

The implementation of the ELM method can be used to predict the water level in Krueng Peusangan by defining the number of hidden layers and input weights that result in the output with the smallest error value. The lowest Mean Square Error (MSE) achieved was 0.063. This result proves that the amount of training and testing data in ELM affects the error value produced, as the ELM method is a training-based approach. Therefore, the more training data available, the better the prediction results obtained. This study highlights the importance of applying machine learning technology, such as Extreme Learning Machine (ELM), in water resource management for the agricultural sector. This technology enables faster and more accurate data analysis and can predict flood risks based on rainfall patterns, river flow, and other environmental factors. Data-driven management strategies have proven to be key in addressing flood challenges, ensuring water use efficiency, and supporting the sustainability of agricultural systems. LM has been implemented to predict various phenomena, including water discharge, water level, and rainfall prediction. ELM accuracy tests are superior to other methods, such as Support Vector Machine (SVM) and traditional artificial neural networks, in predicting river discharge and drought (Parajuli *et al*., 2024).

The integration of monitoring, forecasting, and control is essential to achieving a balance between agricultural water needs and environmental conservation. The implementation of predictive technologies such as ELM can enhance the accuracy of water resource management, particularly in long-term planning to mitigate droughts, floods, and land degradation (Xie *et al*., 2017). This approach aligns with the concept of sustainable water resource management, emphasizing a holistic, data-driven system to minimize the impacts of climate change and pressures on agricultural ecosystems.

3.3 The Comparison Between Predicted and Observed Values

The comparison between predicted and observed values is conducted to evaluate the accuracy of the model in mapping the water level patterns based on historical data. The observed values represent the actual recorded water levels, while the predicted values are the outcomes generated by the model, which is built using input variables. The

Table 2. Comparison results between predictions and observations.

No	Date	Prediction (cm)	Observation (cm)	Absolute Error (cm)	Percentage Error (%)
1	7/01/2023	51.04	49.3	1.74	3.53
2	7/02/2023	50.78	53.7	2.92	5.44
3	7/03/2023	52.01	51.7	0.31	0.60
4	7/04/2023	53.51	53.3	0.21	0.39
5	7/05/2023	51.64	53.7	2.05	3.84
6	7/06/2023	52.92	53.3	0.37	0.70
7	7/07/2023	53.92	53.3	0.62	1.16
8	7/08/2023	53.92	54.3	0.37	0.70
9	7/09/2023	53.72	54.7	0.98	1.79
10	7/10/2023	54.23	55.3	1.07	1.93
11	7/11/2023	55.29	53.3	1.99	3.73
12	7/12/2023	55.10	51.7	3.39	6.58
13	7/13/2023	54.81	54.3	0.51	0.94
14	7/14/2023	55.54	53.3	2.24	4.20
15	7/15/2023	56.17	55.0	1.16	2.13
16	7/16/2023	55.97	56.1	0.12	0.23
17	7/17/2023	55.94	58.3	2.35	4.05
18	7/18/2023	56.57	57.7	1.12	1.96
19	7/19/2023	57.00	58.3	1.29	2.23
20	7/20/2023	56.81	59.0	2.18	3.71
21	7/21/2023	56.90	58.3	1.39	2.40
22	7/22/2023	57.49	59.1	1.60	2.72
23	7/23/2023	57.74	59.5	1.75	2.96
24	7/24/2023	57.61	58.3	0.68	1.18
25	7/25/2023	57.81	59.3	1.49	2.51
26	7/26/2023	58.28	61.7	3.41	5.54
27	7/27/2023	58.42	60.0	1.57	2.63
28	7/28/2023	58.35	60.0	1.64	2.75
29	7/29/2023	58.96	59.7	0.73	1.24
30	7/30/2023	59.04	58.3	0.74	1.27
31	7/31/2023	59.03	56.7	2.33	4.11
32	8/01/2023	59.28	60.0	0.71	1.20
33	8/02/2023	59.56	60.4	0.83	1.39
34	8/03/2023	59.60	60.7	1.09	1.81
35	8/04/2023	59.64	59.8	0.15	0.27
36	8/05/2023	59.89	55.3	4.49	8.30
37	8/06/2023	60.10	60.3	0.19	0.33
38	8/07/2023	60.12	63.3	3.17	5.02
39	8/08/2023	60.20	58.7	1.50	2.56
40	8/09/2023	60.42	58.3	2.12	3.64
41	8/10/2023	60.57	58.3	2.27	3.89
42	8/11/2023	60.60	60.7	0.09	0.16
43	8/12/2023	60.70	58.3	2.40	4.12
44	8/13/2023	60.89	60.0	0.89	1.48
45	8/14/2023	60.89	60.0	0.89	1.48
46	8/15/2023	61.01	61.3	0.29	0.47
47	8/16/2023	61.04	60.0	1.04	1.73
48	8/17/2023	61.15	60.7	0.45	0.74
49	8/18/2023	61.31	61.3	0.01	0.02
50	8/19/2023	61.39	61.7	0.30	0.50
Average		57.43	57.59	1.39	2.39

results of comparing the predicted values with the actual values over the next 7 weeks (Table 2) show that the prediction model has a relatively good accuracy, with errors varying. On certain days, such as 12/8/2023 (0.0943) and 18/8/2023 (0.0108), the model provided results very close to the observed values, indicating accurate predictions. The graph of the predicted water levels is shown in Figure 6. The graph shows the comparison between the predicted values (blue line) and the observed values (red dots) over the next 7 weeks. In general, the prediction pattern follows the trend of the observed values, but there are some differences at certain points. On days such as 12/8/2023 and 18/8/2023, the predicted values closely matched the observed values, indicating high model accuracy. This graph helps in evaluating the performance of the prediction model and determining steps for improving accuracy.

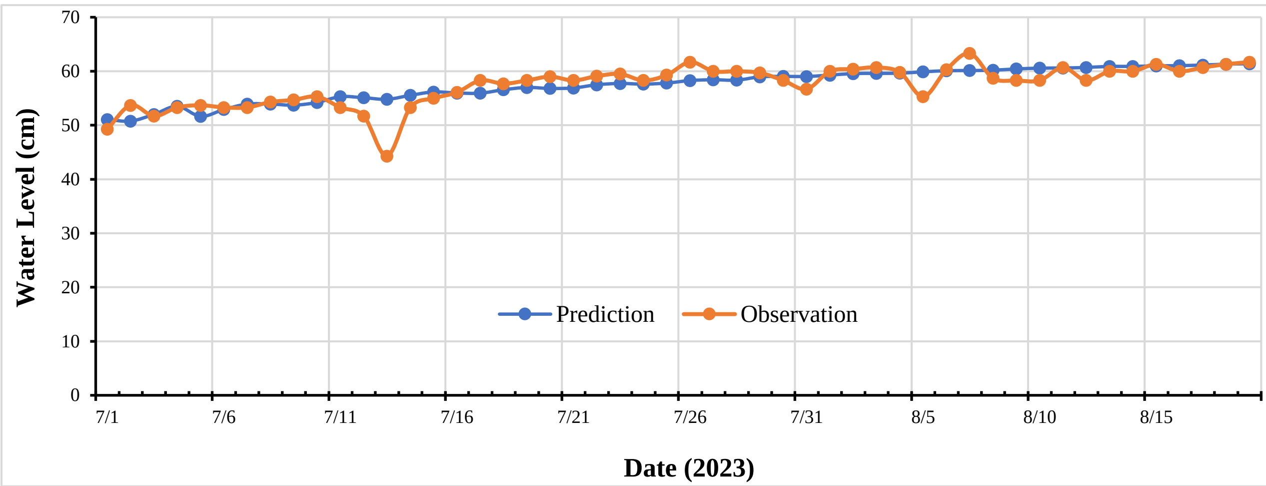


Figure 6. Comparison results between predictions and observations

This study indicates a tendency for an increase in water levels during the first seven weeks of observation. This increase is suspected to be influenced by various factors such as rainfall patterns, regional hydrological conditions, and anthropogenic activities around Krueng Peusangan. However, the recorded water levels remain within the normal range, between 50.78 cm and 61.39 cm, indicating that the water channels or reservoirs still have the capacity to handle the existing flow without causing potential flooding. Therefore, this period can still be considered hydrologically safe.

The use of the Extreme Learning Machine (ELM) method in this study produced satisfactory results in terms of prediction accuracy, with the lowest Mean Square Error (MSE) value of 0.063. The model demonstrated strong predictive performance, with an MSE of 0.063 and RMSE of 0.2511, while the RRMSE is 0.44%, indicating that the model can accurately capture the observed water level variations with minimal relative error. Since an RRMSE value below 10% is generally considered excellent, this result suggests that the model achieves a high level of accuracy and is well-suited for practical applications such as flood forecasting and early warning systems. This model successfully generated predicted values that closely match the actual data, as seen in the graph, which shows a similar pattern between the predicted and observed results. These findings confirm that the quantity of training and testing data significantly affects the model's accuracy. The larger the dataset used for training, the higher the quality of the predictions. Thus, ELM has proven to be an effective machine learning method for modeling water surface levels (Xie *et al*., 2023).

From a contribution standpoint, this research holds considerable value in supporting disaster mitigation efforts, particularly regarding floods that can cause widespread economic and social losses. However, since this study focuses primarily on prediction aspects, further development is needed. In the future, integrating prediction results with early warning systems, decision-making support, and regional planning would be highly beneficial. The presentation of results can also be enhanced by using more interactive data visualizations, making it easier to understand and apply for various stakeholders.

4. CONCLUSION

The Extreme Learning Machine (ELM) method has proven to be effective in predicting water levels in the Krueng Peusangan River Basin (DAS Krueng Peusangan). The predictions for the next 50 days (July–August) show a stable water level during the first 7 weeks, with no signs of significant increases in water levels. The discovered ELM model has proven to be accurate in predicting water levels, with optimal neuron weights providing more precise and effective prediction results. The findings indicate that ELM can produce accurate and optimal predictive models, as evaluated through error analysis using Mean Square Error (MSE). With a well-trained model, the predicted water levels can serve as a basis for water management in the Krueng Peusangan watershed, offering crucial insights for planning and policymaking related to water resource management in the region. These results highlight the importance of implementing advanced machine learning techniques such as ELM and data-driven strategies to support water resource management efforts. This stability forms an important basis for planning more accurate and effective flood management strategies. The success of ELM in predicting water levels supports its application in developing real-time flood early warning systems and long-term water resource planning strategies, especially in flood-prone river basins like Krueng Peusangan. Therefore, it is recommended that future research explores the integration of ELM with remote sensing data and GIS for spatial analysis, and compares its performance with other advanced machine learning models such as LSTM, GRU, or hybrid approaches. Additionally, optimizing ELM parameters using multi-objective algorithms like genetic algorithms or particle swarm optimization could further enhance model robustness. The development of user-friendly decision support tools based on ELM outputs, such as interactive dashboards or mobile applications, is also encouraged to aid local stakeholders and policymakers. These steps will not only improve predictive accuracy but also ensure the practical applicability of ELM in supporting sustainable, data-driven water resource management and disaster risk reduction in the Krueng Peusangan watershed and similar regions.

ACKNOWLEDGMENTS

The authors would like to deliver their gratitude to the Agency for BPDAS Krueng Aceh and this research was funded by Syiah Kuala University of 2024 Fiscal Year with Number 91/UN11.2.1/PG.01.03/SPK/PTNBH/2024.

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