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Determınıng the Water Level of Çamgazi Dam (Adıyaman) Reservoır Usıng Artıfıcıal Intellıgence Methods; A Case Study of Türkiye

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Abstract: *This study aims to predict the water level of the Çamgazi Dam (Adıyaman_Türkiye) reservoir using an advanced convolutional neural network and nonlinear regression approaches on hydrological and meteorological parameters. A long-term hydro-meteorological dataset was employed, and the developed AI model was evaluated with multiple performance metrics. Results show $R^2 \geq 0.96$ for all parameters, indicating high accuracy in predicting water level (elevation), reservoir volume, dimensionless V/h^3 ratio, as well as meteorological variables such as temperature, station pressure, relative humidity, and monthly rainfall. The nonlinear regression model relating the V/h^3 ratio to selected meteorological ratios achieved $R^2 = 0.849$, enabling physically interpretable insights into inter-variable interactions. Under extreme rainfall conditions, the model exhibits systematic under or overestimation and greater scatter at high relative humidity, identified as key limitations. This study highlights the potential of combining AI-based approaches with regression-based empirical models to contribute to related research and planning efforts.*

Keywords: *Convolutional neural network, Reservoir level, Water level prediction, Dam*

INTRODUCTION

Water and water resources are indispensable for all living organisms and the continuity of life. Our country and the Adıyaman province are not considered to be rich in water resources. Therefore, every decision and every action taken regarding the conscious, non-wasteful, and sustainable use of water is of vital importance (Kılıç, 2020; Kılıç, 2021).

Global population growth, rapid urbanization, and changing climate conditions are increasingly driving up the demand for water resources; so making the sustainable management of our precious water resources essential. One aspect of studies in this field is determining the water level of dam reservoirs. Accurately and reliably estimating and identifying the water level of dam reservoir is critically important both for the efficient use of current water potential and for reducing flood and drought risks (Azad et al., 2022; Rehamnia and Mahdavi, 2025). Results obtained using hydrological observations and data help in water resource planning, sustainable water use, determining water levels in dam reservoirs, designing water structures and water works, and improving the operating conditions and safety of dams. Many parameters (stream, climate, evaporation, seepage, sediment transport, etc.) affect water resources and the water level in the dam reservoir, and accurately determining these conditions is crucial for all water structures, and especially for dam reservoir management and dam operation. Accurate estimation of the available water quantity in dams by determining the water level in the reservoir at various time intervals using historical records is essential for many aspects, including irrigation, energy production, flood control, drinking water supply, drainage, the design and construction of water structures, and dam reservoir management. Water level measurements in dams can be determined using complex models that take into account hydrological and hydrometeorological parameters such as precipitation, flow, humidity, and temperature. Changes in reservoir levels are the complex result of numerous environmental factors; including precipitation, direct and indirect flow from neighboring basins, evaporation from water surface, air-water temperature, and interactions between low-lying aquifers. Reservoir level parameters include water inflow into the reservoir, water storage in the reservoir, water outflow from the reservoir, evaporation, soil moisture, and infiltration (Ouyang et al., 2025)..

Especially in semi-arid to arid regions like Adıyaman, where climatic conditions are challenging, the development of decision support systems for reservoir management becomes even more crucial, considering the limited and variable nature of water resources. One such decision support system involves making predictions by periodically conducting hydrological observations. Obtaining hydrological data solely through classical methods is costly, laborious, and time-consuming. Furthermore, since this data can change frequently over short periods, measuring it accurately according to standards is becoming increasingly difficult today. Therefore, to simplify the process, reduce costs, decrease labor, obtain data closer to standards, and save time, statistical methods and new modeling techniques are needed for data that cannot be measured, are incomplete, or are measured incorrectly. Artificial intelligence methods, one of these current techniques, are widely used and continue to be used in hydrology and water resource systems, engineering studies dealing with water science, determining water levels in dams, and modeling complex nonlinear events (Kermani & Kheimi, 2026; Kambarbekov et al., 2024). Hydrological modeling, within this scope, is a critical tool for efficiently managing water resources, especially in regions where water scarcity is a major problem and where climatic conditions are semi-arid to arid, such as Adıyaman. Hydrological models use mathematical equations to simulate the behavior of the water cycle in events such as precipitation, evaporation, surface flow, and groundwater recharge. Artificial intelligence–based hydrological models hold great promise in improving the accuracy of hydrological predictions, estimating reservoir water levels, and supporting sustainable water management applications (Shen, 2018). Most studies in the literature have shown that the use of artificial intelligence methods in determining water levels in dam reservoirs yields positive results (Özdoğan et al., 2023; Tongbi et al., 2024). Integrating artificial intelligence into technologies such as remote sensing allows for the periodic monitoring of water slough, basin areas, and water reservior. Computer analysis of satellite imagery helps in understanding changes in reservoir water levels and determining reservoir water management (Baigang et al., 2022).

In recent years, numerous studies in the literature have successfully applied artificial intelligence techniques – artificial neural networks (ANNs), machine learning, deep learning, etc. – to model the relationship between meteorological variables and reservoir behavior. In particular, time series-based hybrid models (SARIMA-ANN), long-short-term memory networks (LSTM), and swarm intelligence-based integrated machine learning methods have been shown to provide high accuracy in reservoir water level and volume prediction (Li et al., 2023). Furthermore, it is emphasized that integrated modeling approaches that consider the dynamic interaction between reservoir level and hydro-meteorological inputs such as precipitation and temperature yield effective results both in more realistically representing reservoir behavior and in evaluating dam safety (Gou et al., 2024). These studies demonstrate that data-driven approaches offer a more flexible and adaptable modeling infrastructure compared to traditional methods.

Located within the borders of Adıyaman province, the Çamgazi Dam plays a significant role in the agricultural irrigation and other water needs of the region. The region's semi-arid climate, the high temporal and spatial variability of rainfall, and the potential effects of climate change make predicting the water level in the reservoir difficult. Traditional deterministic and statistical methods are often insufficient for modeling such complex and nonlinear hydrological processes. Therefore, in addition to these classical methods, the use of artificial intelligence-based approaches capable of pattern learning from large datasets and capturing complex relationships is becoming increasingly important (Li et al., 2023; Unes et al., 2019). Determining and estimating surface water reserves in regions with climate conditions and similar topographical features where water loss due to evaporation, is significant is crucial for the sustainable use of water.

This research aims to predict hydrological (h, V, V/h^3) and meteorological (T_2, SP_2, RH_2, P_m) parameters of Çamgazi Dam proposing an advanced convolutional neural network (CNN) based model and a nonlinear regression approach. In this context, a long-term hydrometeorological dataset obtained from the dam site was used, and the developed artificial intelligence model was evaluated with various performance metrics (RMSE, MAE, R^2). The results showed that $R^2 \geq 0.96$ was achieved for all parameters, thus demonstrating that the proposed advanced convolutional neural network model based on artificial intelligence could produce highly accurate predictions for meteorological variables such as water level, reservoir volume, and dimensionless V/h^3 ratio, as well as relative humidity, temperature, station pressure, and monthly precipitation.

This research show that artificial intelligence-based approaches, together with regression-based empirical models, can be used in dam operation, flood, drought management, sustainable water use, and water resources planning. This study has the potential to contribute to the more optimal, ideal, and efficient use of the existing water in Çamgazi Dam, regional water resources planning, the regional economy, and methodological frameworks that can be applied in basins with similar climatic characteristics.

MATERIALS AND METHOD

Research Area

The Çamgazi Dam, one of the units of the Adıyaman-Kahta project, which is among the 13 major projects within the Southeastern Anatolia Project (GAP), was constructed between 1990 and 1999 on the Doyran River for irrigation purposes. Located approximately 17 km from the Adıyaman city center and 2.5 km northeast of Çamgazi village, it is built on the Doyran and Kuzgun rivers, and receives water from the Kırkgöz and Çakal rivers during the winter and spring months.

The dam, which is of the earth embankment type, has a body volume of 5.512,000 m³, a height of 45.00 m from the riverbed, a reservoir volume of 56.17 hm³ at normal water level, and a reservoir area of 5.55 km² at normal water level. The dam provides irrigation services to an area of 6.532 hectares (http://bolge20.dsi.gov.tr). Location map of Çamgazi Dam is seen in Figure 1.

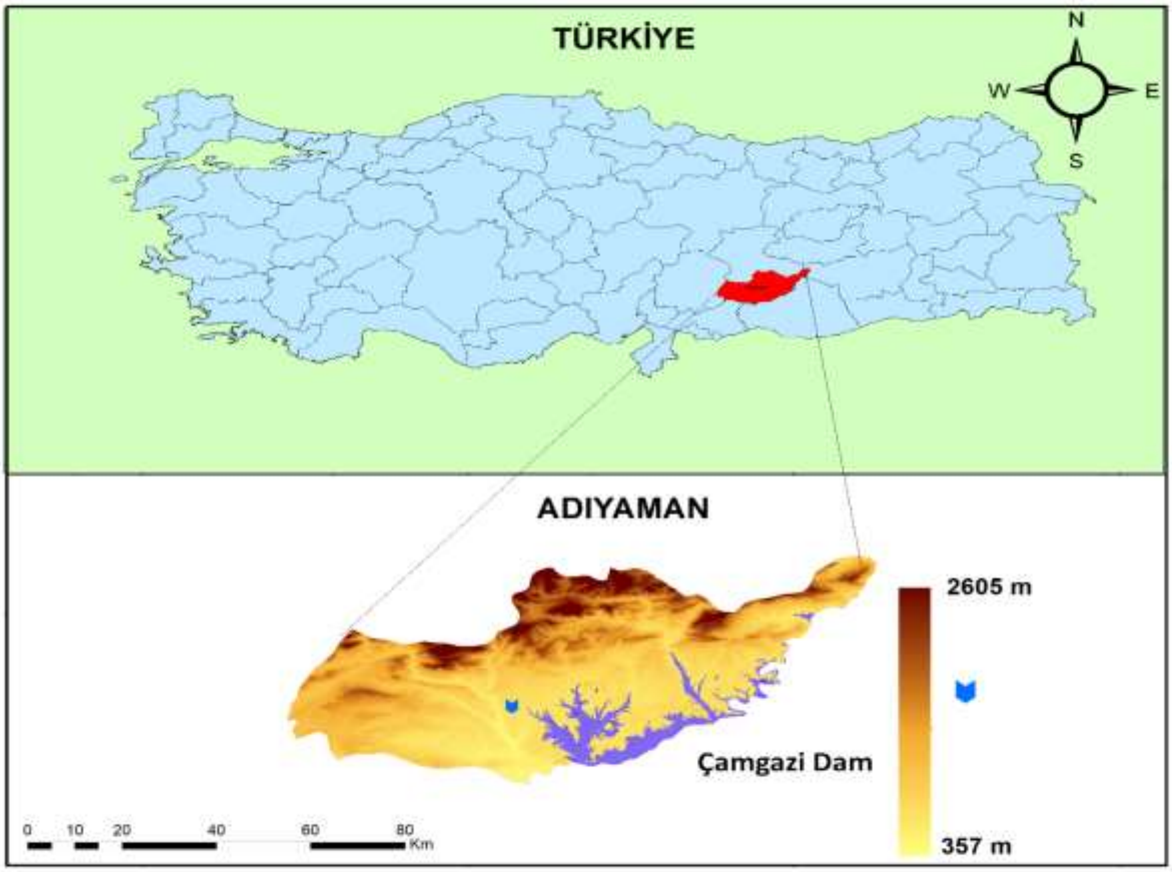

Figure 1. Location Map of Çamgazi Dam

View of Çamgazi Dam is seen in figüre 2. Field observations revealed that factors such as the large surface area of the reservoir, insufficient rainfall, and high evaporation loss have lowered the water level, causing it to fall below the desired level (Figure 3,4).

Figure 2. View of Çamgazi Dam (www.google.com/images).

Figure 3. Çamgazi Dam water level and previous water-level marks on the embankment (Z.Kılıç)

Figure 4. Spillway approach channel and current water level (Z.Kılıç)

Data and Datasets

In this study, regression analyses were performed using monthly water level and reservoir volume data from the State Hydraulic Works (DSİ) and monthly temperature, precipitation, and humidity measurement data from the General Directorate of Meteorology for the years 2018-2024. In the hydrological model to be created to determine the water level change and reservoir volume of Çamgazi Dam, monthly evaporation rate and monthly water level/volume measurement data from the previous month were used as inputs. All datasets were compiled at the monthly time step, and before inclusion in the analysis, missing observation checks, outlier analysis, and consistency tests were performed. Missing data were completed based on the long-term monthly averages of the relevant variable.

Nonlinear Regression Analysis

Nonlinear regression is a statistical method preferred when the relationship between the dependent and independent variables cannot be adequately represented by a linear function. The analyses in this study were performed using IBM SPSS Statistics software. The *Levenberg–Marquardt* algorithm was chosen for the parameter estimation process; this algorithm is widely preferred in nonlinear regression applications because it reduces sensitivity to initial parameter values and minimizes the risk of getting stuck in a local minimum. Initial parameter values were determined using preliminary correlation analyses and physical expectations.

The Proposed Method

This research implements an advanced Convolutional Neural Network (CNN) designed to automate the extraction of latent patterns from peak hydrological and meteorological data measurements, bypassing the need for manual feature engineering common in traditional machine learning. To ensure model stability, the input signal undergoes rigorous preprocessing where extreme outliers are neutralized and replaced with local arithmetic means before being normalized. The architecture functions through localized receptive fields that mimic biological sensory processing, utilizing a sliding window mechanism and kernel matrices to mathematically calculate impulse responses across the dataset.

These localized features are synthesized into representational vectors via dot product operations and optimized through a backpropagation algorithm. An activation function, as shown in equation (1), is applied to the neurons with rectified linear units (ReLUs) based on the original data.

$$f(x) = \max(x, 0) \tag{1}$$

Following the network's activation and fine-tuning, the max pooling layer reduces the dimensionality of the feature maps by extracting the most prominent values from localized regions, which enhances computational efficiency and spatial invariance. The model's predictive performance, governed by its internal weights, is optimized through gradient descent, an entropy loss-based minimization technique that iteratively adjusts parameters to reduce the variance between forecasts and observations. To evaluate and guide this optimization, the cost function is formally defined as equation (2).

$$L(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y^{(i)}\log\left(h_\theta\left(x^{(i)}\right)\right) + (1 - y^{(i)})\log(1 - h_\theta\left(x^{(i)}\right))] \tag{2}$$

This equation represents the cross-entropy loss, where m is the number of training samples, y is the actual label, and $h_\theta(x)$ is the predicted probability. By minimizing this value, the CNN refines its connection weights to maximize the accuracy of the hydrological and meteorological data forecasting results.

The relationship between predicted and actual output vectors for a given class, denoted by M, is represented by z_j and d_j= (0,…,0,1,$\overset{k}{\rightarrow}$ ... 1,0,…,0), respectively. This vector is a one-hot encoded vector where the c-th element is 1 and all other elements are 0. This formulation in Equation (3) results in a softmax activation for the CNN's output layer.

$$z_j^{(i)} = \frac{e^{f_j}}{\sum_{i=1}^{M} e^{f_i}} \tag{3}$$

To prevent the model from overfitting and to ensure numerical stability during training, a weight regularization term is integrated into the objective function. This addition modifies the primary loss function $L(\theta)$ by penalizing large weight magnitudes, effectively discouraging the network from becoming overly complex or sensitive to noise in the hydrological and meteorological data. The regularized cost function, as expressed in equation (4).

$$L_{reg}(\theta) = L(\theta) + \sigma\Omega(w) \tag{4}$$

In this expression, σ represents the regularization strength, a hyperparameter, and $\Omega(w)$ denotes the regularization penalty most commonly the L_2 norm (squared magnitude) of the weights. By incorporating this factor, the optimization process seeks a balance between minimizing prediction error and maintaining small weight values, which promotes better generalization to unseen data. A CNN architecture, combining both 3D and 2D convolutional networks, was proposed for feature extraction as shown in Figure 3. As illustrated in the schematic, raw information first enters a refinement stage where it is scaled and standardized to ensure consistency. Following this preparation, the signal traverses a sequence of eight deep volumetric operators. These elements utilize multi-dimensional kernels to scan across height, width, and depth simultaneously, with the density of these kernels dictating the richness of the resulting feature maps. To bridge the gap between high-dimensional tensors and flattened arrays, the system executes a structural reconfiguration, translating the 3D grid into a 2D format compatible with standard spatial layers. This specific design choice ensures that the model preserves chronological or depth-based relationships while utilizing the high-speed pattern recognition inherent in 2D processing. To prevent the model from simply memorizing training noise, stochastic regularization units, known as dropout, are interspersed between the volumetric and planar modules. The secondary phase involves 2D layers equipped with 32 and 64 sensing units to synthesize incoming variables. Interestingly, the architecture loops back into a 3D state to fuse disparate data points before transitioning into a max-pooling stage, which distills the 2D slices extracted from the 3D blocks. To maintain high fidelity and combat the loss of information across deep layers, skip connections funnel raw feature data directly into a concatenation hub. By utilizing a specific arrangement of two 3D blocks and a single 2D unit, the system minimizes resource consumption and filters out repetitive data. Once the dimensions of all feature matrices are synchronized, they are merged and fed into dense, fully connected layers to calculate the terminal prediction. The proposed scheme for hydrological and meteorological data prediction process is seen in Figure 5.

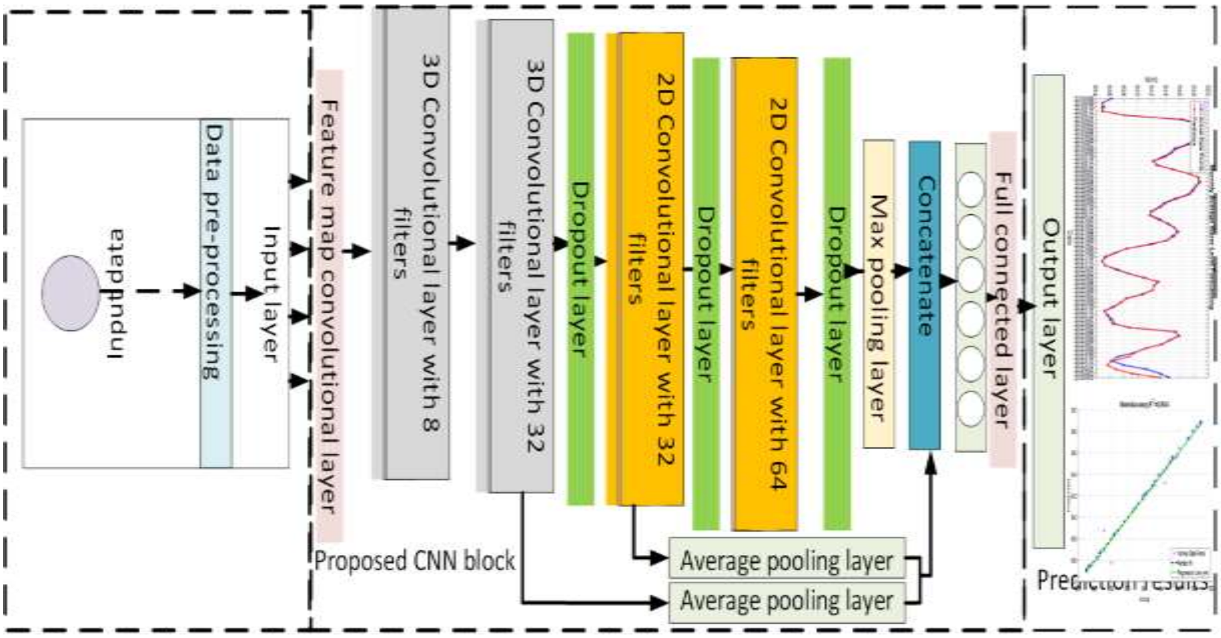

Figure 5. The proposed scheme for hydrological and meteorological data prediction

Evaluating Model Performance

The predictive performance of the developed model was evaluated using four different statistical measures (coefficient of determination, R^2; avarae absolute error, MAE; avarage of $x^{1/2}$ square error, RMSE; and scatter index, SI).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{y})^2} \tag{1}$$

$$\text{MAE} = \frac{|x_i - y_i|}{x_i} \tag{2}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{3}$$

$$\text{SI} = \frac{\text{RMSE}}{\bar{x}} \tag{4}$$

RESULT AND DISCUSSION

This study aimed to predict the water level in the reservoir of Çamgazi Dam, located within the central district of Adıyaman province, by analyzing hydro-meteorological data using statistical and proposed convolutional neural network methods. The performance of the developed models was evaluated using various error metrics (RMSE, MAE, and R^2). The developed prediction models were tested on seven basic parameters: water level (h), reservoir water volume (V), dimensionless ratio (V/h^3), monthly average temperature (T^2), station pressure (SP^2), relative humidity (RH^2), and monthly total precipitation (P_m). According to the performance metrics summarized in Table 1, a high prediction accuracy of $R_2 \geq 0.96$ was achieved for all parameters.

Table 1. Performance Results of Prediction Models

Parameteres	RMSE	MAE	R^2
h	0.8319	0.3328	0.9636
V	1.5646	0.6705	0.9868
V/h^3	0.0126	0.0050	0.9674
T_2	0.5991	0.4445	0.9958
SP_2	0.5297	0.2843	0.9856
RH_2	2.6696	1.0790	0.9789
P_m	15.3467	6.8760	0.9660

Evaluation of Water Level (h) Prediction Results:

When examining the change in the monthly average water level over time, it is observed that the *h* values reach levels of 648–649 m during rainy periods and decrease to the 635–637 m range during dry periods, so it is exhibiting a significant seasonal fluctuation (Figure 6a). The model prediction curve successfully follows these cycles in general. Although it is observed that the model shows a partial phase error or amplitude suppression effect in transition phases where rapid water level changes occur, this reflects the natural difficulties in modeling sudden hydrological changes. Indeed, in the scatter plot in figure 6b, it is seen that the majority of the data points are concentrated around the reference line ($y=x$).

The obtained $R^2=0.9636$, RMSE=0.831 m and MAE=0.3328 m values prove the high generalization capacity of the model. Considering that in the literature, the R^2 values of artificial neural network (ANN) based models developed for various dams in Türkiye, generally remain in the range of 0.91–0.95 (Kişi et al., 2015), it can be said that the current model exhibits superior performance in water level prediction.

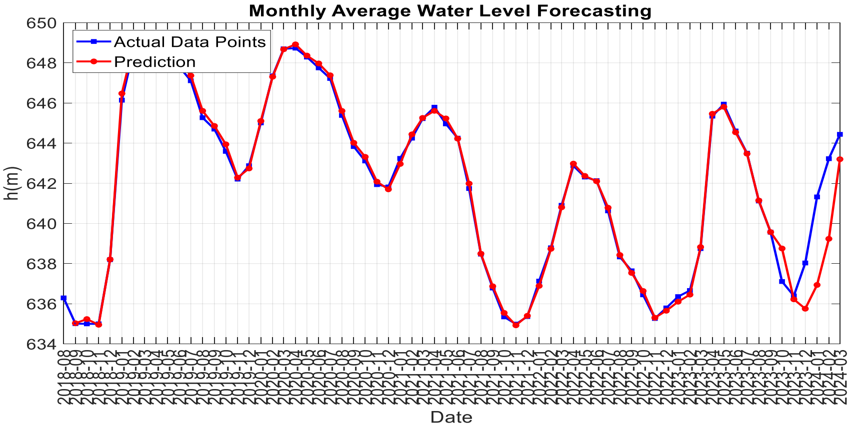

Figure 6a. *h* Forecating Result

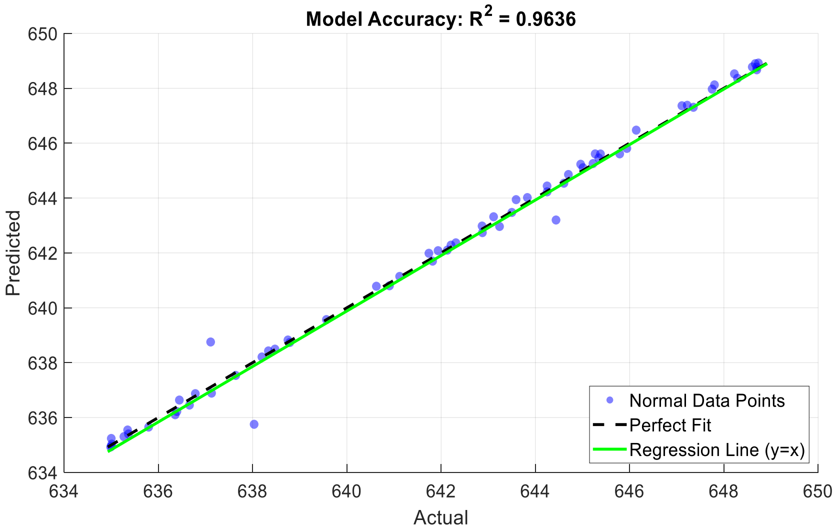

Figure 6b. Scattered plot of *h* Forecating Result

Reservoir Volume (V) and Dimensionless Ratio (V/h^3) Prediction Performance:
The monthly average reservoir volume fluctuates within a wide range between 8 hm³ and 52 hm³, consistent with the water level (Figure 7a). The model predicts both rapid increases in water level during winter and spring months and volume losses during summer months with high accuracy. In particular, the R^2 value of 0.9868 achieved for *V* estimation indicates the highest prediction accuracy among all parameters (Figure 7b). Considering that a similar reservoir level and inflow forecasting study using long short-term memory (LSTM) networks in the literature reported R² values up to about 0.96 (Zhang et al., 2021), the results obtained in this study are extremely successful.

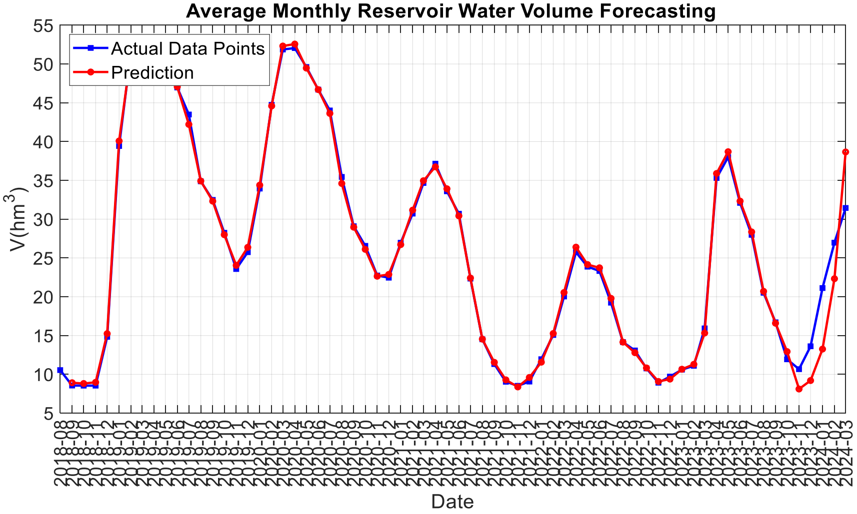

Figure 7a. *V* Forecasting Result

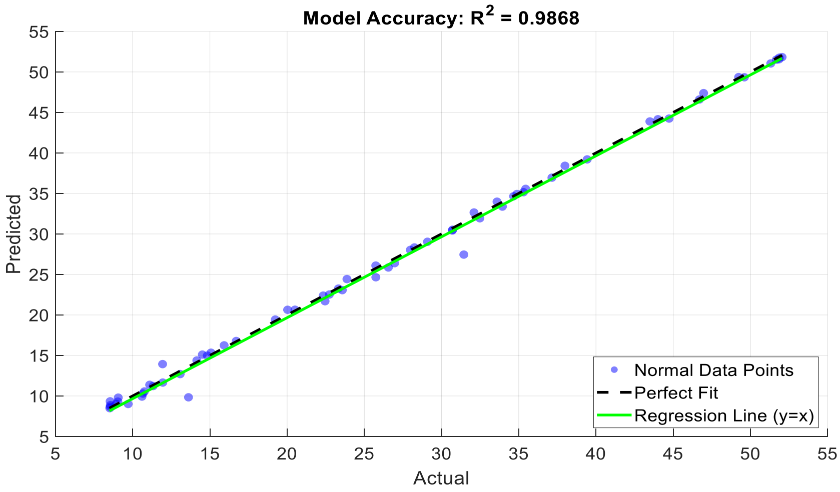

Figure 7b. Scattered plot of *V* Forecasting Result

Similarly, a high success rate (R^2=0.9674) was achieved in predicting the V/h^3 ratio, which represents the bathymetric characteristics of the reservoir (Figure 8a, 8b). It has been observed that the ratio generally fluctuates between 0.05 and 0.18, but occasionally forms peaks approaching the 0.50 level. The model successfully learned all geometric fluctuations except for these extremes; this demonstrates that the reservoir's volume-level relationship can be reliably formulated using data-driven methods.

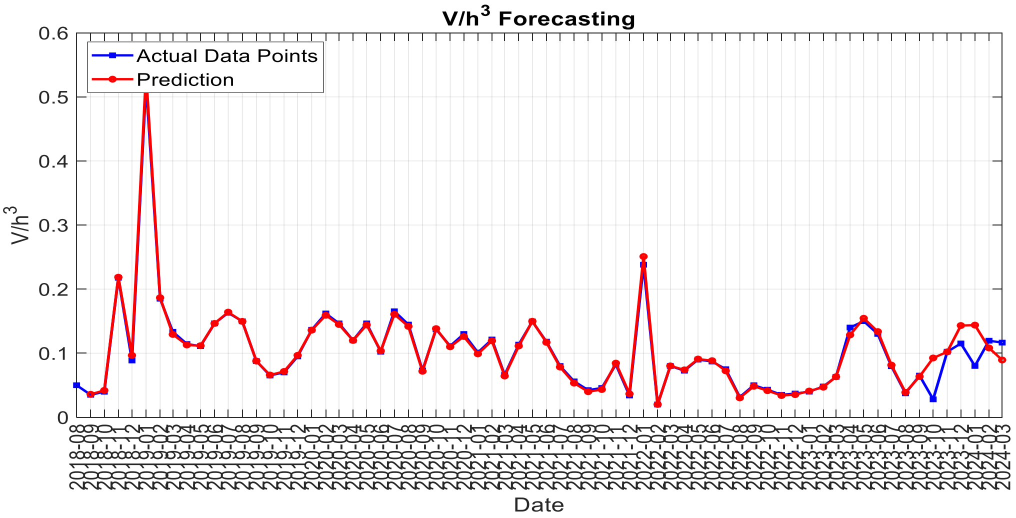

Figure 8a. ***V/h³*** **Forecasting Result**

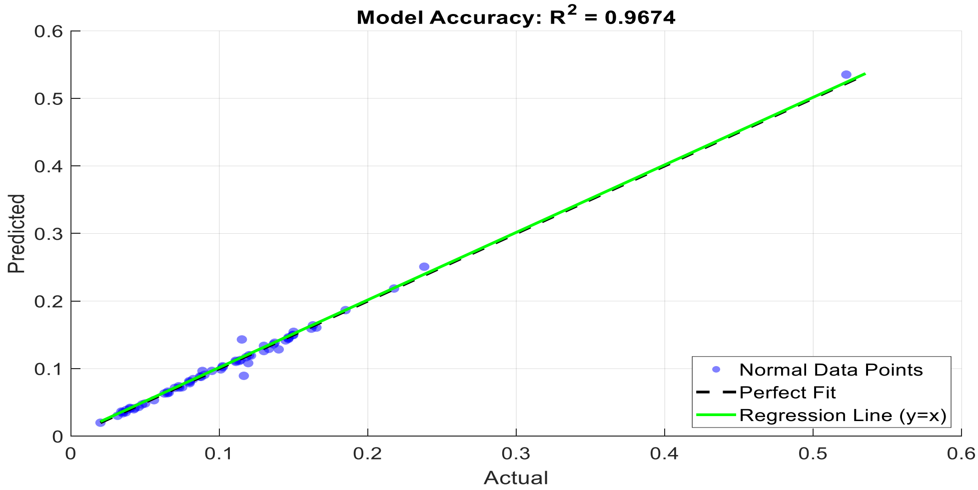

Figure 8b. Scattered plot of ***V/h³*** **Forecasting Result**

Prediction Performance of Meteorological Parameters (T_2, SP_2, RH_2):

Monthly average temperature (T_2) was one of the easiest variables to learn from by the model due to its regular seasonal periodicity (Figure 9a). The near-perfect overlap between the prediction and observation curves, and the clustering of points on a linear line in the scatter plot (Figure 9b), are supported by the calculated R^2=0.9958 and RMSE=0.5991 values. This result surpasses the prediction accuracies (R^2=0.97–0.98) obtained by Radhika and Shashi, using support vector machines (Radhika & Shashi, 2009).

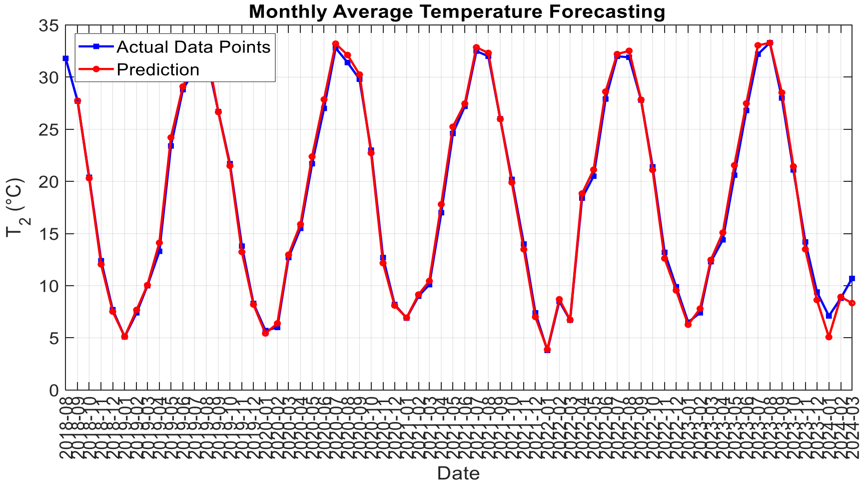

Figure 9a. T_2 Forecasting Result

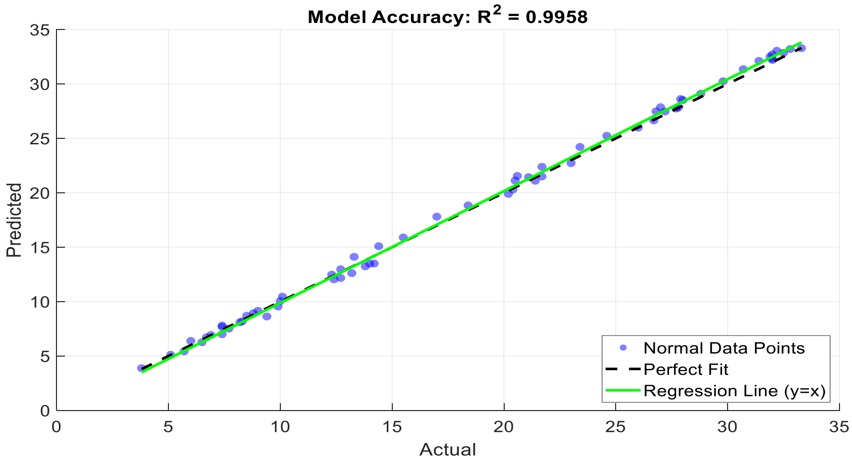

Figure 9b. Scattered plot of T_2 Forecasting Result

Station pressure (*SP_2*) shows a relatively regular seasonal pattern, fluctuating between 928–945 hPa. Pressure values are relatively low during the summer months, while reaching high values during the autumn and winter periods. The model prediction curve follows these seasonal fluctuations with high accuracy; only a few transitional periods show small phase shifts at peak or trough points. The R^2=0.9856 performance obtained for *SP_2* also shows that the model can track seasonal atmospheric changes with great accuracy (Figure 10a, 10b).

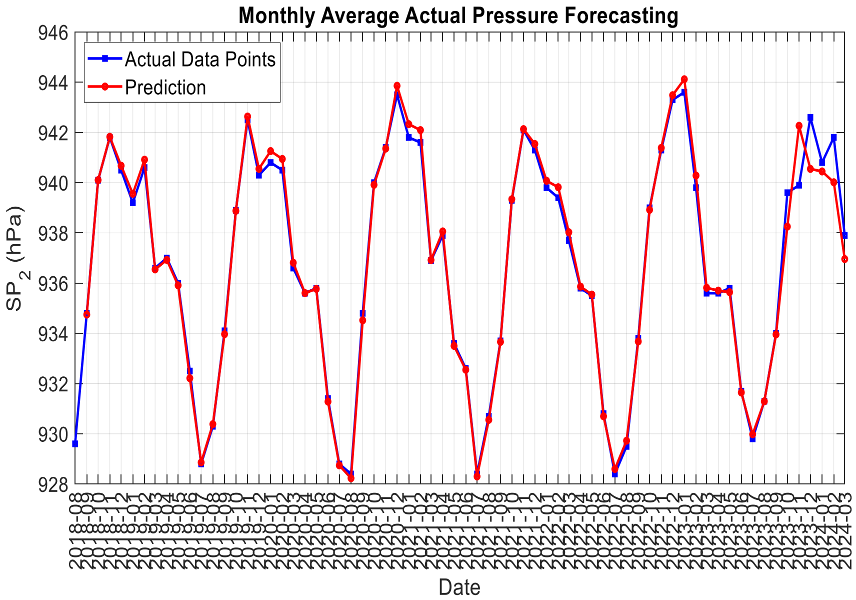

Figure 10a. SP$_2$ Forecasting Result

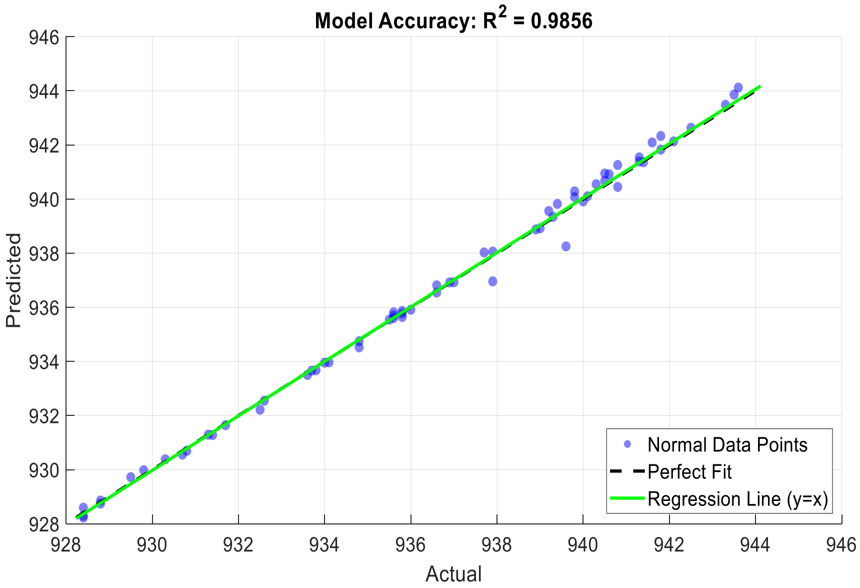

Figure 10b. Scattered plot of SP$_2$ Forecasting Result

Monthly average relative humidity (*RH_2*), on the other hand, follows a seasonal cycle inversely proportional to temperature (Figure 11a), and is a relatively more difficult parameter to model, as it is particularly affected by dynamics such as convective precipitation and local evaporation.

Nevertheless, values such as R^2=0.9789 and RMSE=2.6696 were achieved; while quite accurate predictions were produced under moderate and low humidity conditions, the expected increase in scattering was observed at extreme humidity levels (60-85%) (Figure 11b). This performance is consistent with the high accuracy levels (R^2 up to ~0.9 and above, depending on site/setting) reported in relative humidity forecasting studies using machine-learning approaches (Chattopadhyay & Chattopadhyay, 2008).

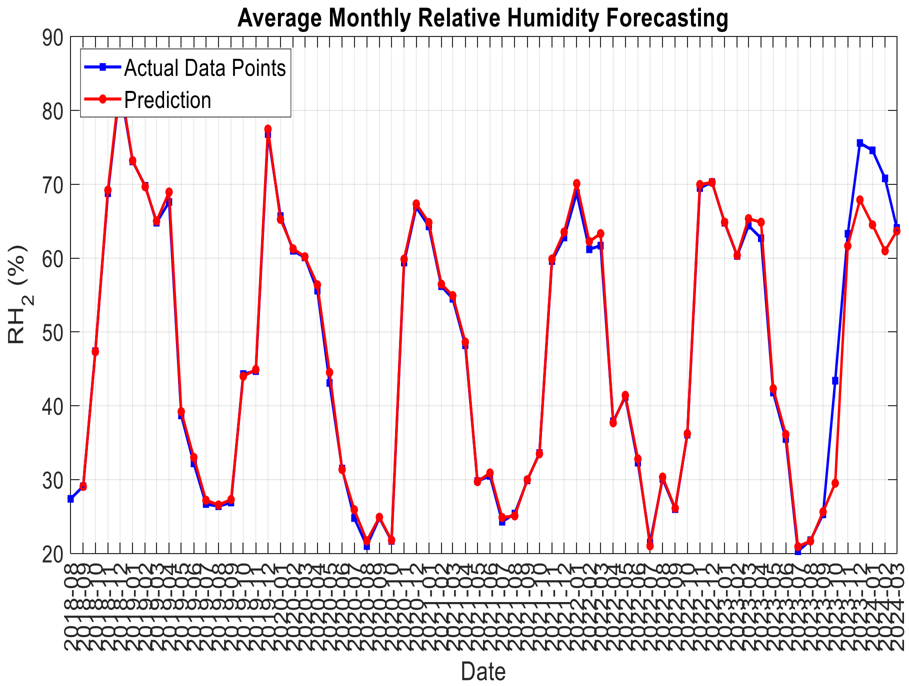

Figure 11a. RH$_2$ Forecasting Result

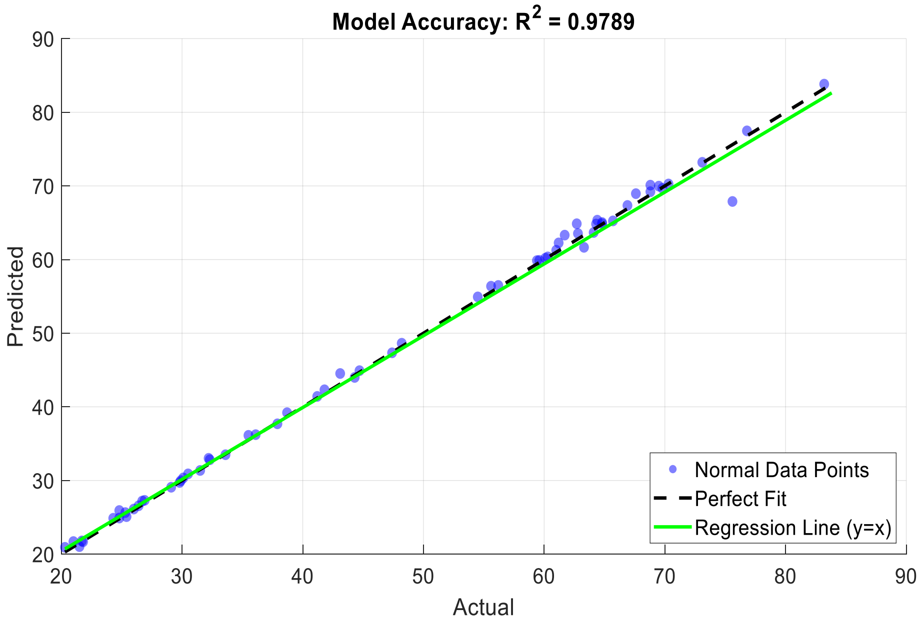

Figure 11b. Scattered plot of RH$_2$ Forecasting Result

Monthly Total Precipitation (P_m) Prediction Performance:

Figure 12a shows the coexistence of long dry periods and extreme precipitation peaks reaching 200–350 mm. The model predicted dry and moderately rainy months with high accuracy. The systematic underestimation trend observed in high-precipitation peaks (Figure 12b) is due to the limited number of these extreme events in the training set and nonlinear hydroclimatological interactions.

Despite this limitation, the R^2=0.966 and RMSE = 15.3467 mm values obtained for monthly total precipitation (P_m) are higher than the results reported in similar monthly precipitation prediction studies using soft computing methods, which typically achieve R^2 values around 0.92–0.95 (Kişi & Shiri, 2011).

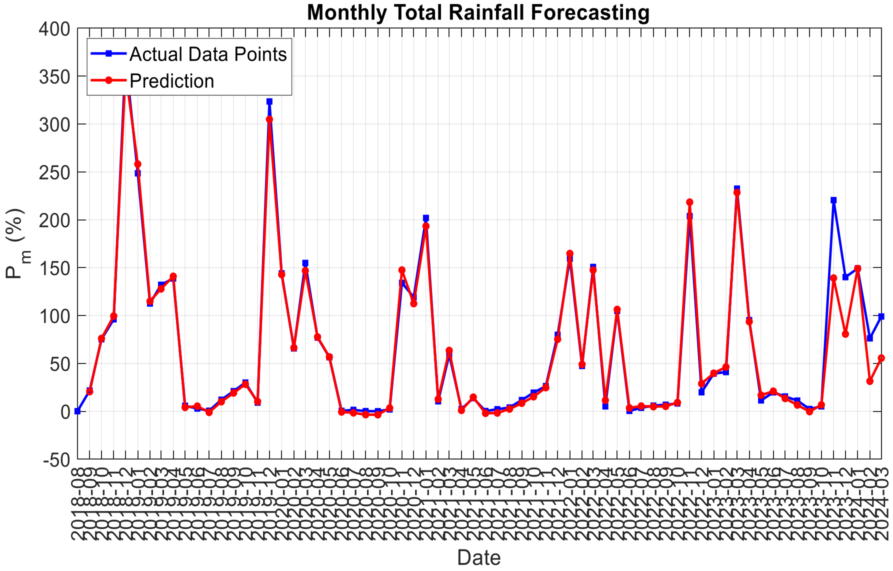

Figure 12a. ***P_m* Forecasting Result**

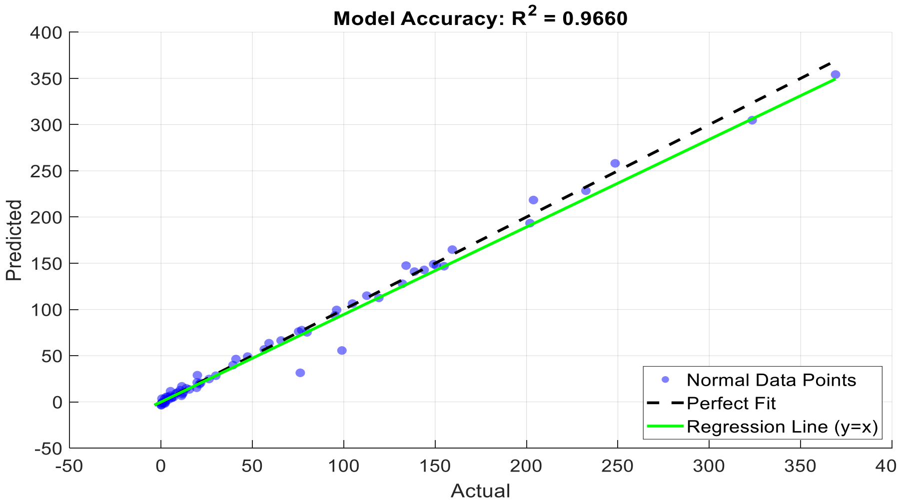

Figure 12b. *Scattered plot of P_m Forecasting Result*

As a result of nonlinear regression analysis, Equation (5) was obtained, which describes the functional relationship between the V/h^3 ratio and the selected meteorological variables. In this equation, V/h^3 is used as the dependent variable; and the proportional expressions derived from temperature, wind speed, relative humidity and precipitation variables are used as independent variables.

The model structure was determined by considering both the level of statistical fit and the physical consistency with hydrometeorological processes.

$$\frac{V}{h^3} = \left(\frac{T_3}{T_2} - 1.939\right)\left(\frac{WS_3}{WS_2} - 5.314\right)\left(\frac{RH_1}{RH_2} - 0.200\right)\left(\frac{P_m}{P_{m,a}} + 2.984\right) + 0.119 \qquad (5)$$

The performance metrics calculated for this equation are R^2= 0.849, MAE=0.280, RMSE=0.063, and SI=0.362. Accordingly, the model can explain approximately 85% of the total variance and represents the V/h^3 ratio with acceptable accuracy. The fact that the error metrics are low in absolute value but higher compared to the values obtained with AI-based prediction models indicates that the nonlinear regression approach partially captures the system dynamics but is not as successful as data-driven (AI) methods in explaining complex hydrometeorological processes.

The ratio terms used in equation 1 also offer important clues from a physical interpretation perspective. It shows that the relative increase in maximum temperature to the monthly average temperature has an effect on V/h^3. Similarly, considering the ratio of maximum wind speed to average wind speed, high wind speeds disperse the saturated air layer above the water surface, increasing moisture transfer and open water surface evaporation; this indirectly affects the reservoir's volume-level relationship in the long term. The ratio of minimum relative humidity to average humidity and the indirect effects of dryness/aging conditions on the reservoir geometry are reflected in the model. It is shown that the deviation of the relevant month's precipitation from the long-term manual precipitation average has a significant effect on the V/h^3 ratio.

The multiplicative structure of equation 5 shows that the interactions between the ratios T_3/T_2, WS_3/WS_2, RH_1/RH_2, and $P_m/P_{m,a}$ combine in a nonlinear manner. This confirms that the hydrometeorological processes in the dam basin do not develop independently, but rather under simultaneous and combined effects. However, the fact that the R_2 value is below the 0.96-0.99 range obtained in artificial intelligence models reveals that such closed-form empirical equations have limited representational power, especially under extreme conditions. Nevertheless, the provision of a reasonable level of explanatory power with a relatively simple mathematical structure shows that equation 5 is a usable tool for rapid prediction and approximate calculations in engineering applications.

Overall, this relationship derived by nonlinear regression provides a physically meaningful and interpretable framework regarding the direction and relative effects of the relationships between the V/h_3 ratio and the selected meteorological variables. However, the error metrics and explanatory power suggest that, particularly in sensitive decision-making processes such as dam operation and risk management, this equation should be considered more as a "supportive/assistive" tool in conjunction with artificial intelligence based models rather than used alone.

CONCLUSION

When the developed artificial intelligence based models are evaluated together with the empirical correlations obtained through nonlinear regression analysis, it is seen that the multivariate hydro-meteorological system of Çamgazi Dam and its surroundings can be represented with a significant level of accuracy. The fact that the artificial intelligence based model achieved an $R_2 \geq 0.96$ value for all parameters reveals that predictions with high reliability were produced for both hydrological (h, V, V/h_3) and meteorological (T_2, SP_2, RH_2, P_m) variables. Comparisons with similar studies in the literature show that the accuracy levels obtained in this study are in most cases higher than existing results, and confirm that the developed artificial intelligence model is a powerful method for dam-scale hydro-meteorological predictions.

On the other hand, the fact that the equation obtained through nonlinear regression analysis, relating the V/h_3 ratio to meteorological rates, has acceptable performance indicators such as R_2=0.849, MAE=0.280, RMSE=0.063, and SI=0.362, reveals that models based on simpler mathematical structures also achieve a certain success in explaining the reservoir volume-elevation relationship. However, the explanatory power and error metrics of this equation remain lower when compared to artificial intelligence models; this highlights the superiority of data-driven approaches in representing complex and nonlinear hydrometeorological processes. Nevertheless, since this regression equation provides a physically interpretable framework for the direction and relative importance of interactions between variables, it serves as a practical and complementary tool for rapid prediction and approximate calculations in engineering applications.

When all the findings are evaluated together, it can be said that artificial intelligence-based models can be used as a strong alternative or complementary component to traditional physical models in areas such as dam operation, flood prediction, sustainable water use, and water resources planning. However, the systematic underestimation trend observed in sudden rainfall events and the increasing scattering in the high-value region of relative humidity reveal that the model has certain limitations under extreme conditions.

In order to reduce these limitations, it is suggested that future studies should: (i) analyze the model performance separately according to seasonal and extreme conditions, (ii) increase the interpretability of the model by determining the sensitivity and importance order of the input variables, and (iii) evaluate the future water potential of Çamgazi Dam by conducting integrated scenario analyses with climate projections.

In conclusion, this study demonstrates that the combined use of artificial intelligence and empirical regression approaches has significant potential in the integrated modeling of multivariate hydrometeorological systems and can be effectively evaluated in decision support processes for water resources management.

Symbols:

h: Monthly average water level (m)
V: Monthly average reservoir water 38rojec (hm^3)
T_1: Monthly minimum temperature (°C)
T_2: Monthly average temperature (°C)
T_3: Monthly maximum temperature (°C)
$T_{ave,1}$: Monthly average minimum temperature (°C)

$T_{ave,3}$: Monthly average maximum temperature (°C)
SP_1: Monthly minimum actual station pressure (hPa)
SP_2: Monthly average actual station pressure (hPa)
SP_3: Monthly maximum actual station pressure (hPa)
WS_2: Monthly average wind speed (m/s)
WS_3: Monthly maximum wind speed (m/s)
RH_1: Monthly minimum relative humidity (%)
RH_2: Monthly average relative humidity (%)
RH_3: Monthly maximum relative humidity (%)
P_m: Monthly total precipitation (manual) (mm)
P_o: Monthly total precipitation (mm)
$P_{m,a}$: Monthly total rainfall (manual) average (mm)

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