



DEEP LEARNING APPROACHES FOR SEASONAL PRECIPITATION AND RUNOFF PREDICTION: A CASE STUDY OF TAQTAQ-DOKAN BASIN

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Abstract: The TaqTaq-Dokan River Basin on the Little Zab River in northern Iraq faces seasonal water shortages in summer and recurrent flooding in winter due to high runoff downstream of Dokan Lake. To address this, this study applied deep learning neural network models to forecast annual precipitation and estimate surface runoff up to 2030. Monthly rainfall data from Koya Meteorological Station for 1987–2024 were used to model runoff via the Soil Conservation Service Curve Number method. Five deep learning architectures Multilayer Perceptron, Convolutional Neural Network, Recurrent Neural Network, Long Short-Term Memory, and Gated Recurrent Unit were trained on 70% of the data and tested on 30%. Model performance was evaluated using MSE, RMSE, MAE, AIC, and BIC. Results show RNN outperformed other models with the lowest errors (MSE = 1009.65, RMSE = 31.78, MAE = 23.09), followed by CNN, LSTM, GRU, and MLP. Forecasts indicate a consistent seasonal pattern: peak rainfall and runoff occur in winter, with zero runoff from June to September. The observed average annual runoff for 1987–2021 was 396.56 million m³, while the predicted runoff for 2024–2030 averages 331.37 million m³ annually. The findings confirm that substantial rainfall water over 330 million m³ per year—is discharged unused into the Little Zab River. The study concludes that applying deep learning algorithms is a reliable tool to predict the annual precipitation and surface runoff in TaqTaq-Dokan basin. Consequently, this study recommends that relevant organisations in Iraq take necessary actions and implement strategic plans and policies to conserve water by constructing ponds, dams, and reservoirs in areas with high precipitation.

Keywords: TaqTaq-Dokan basin, Precipitation forecasting, Runoff estimation, Deep learning architectures, Hydrological modelling

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1. Introduction

Over recent decades, northern Iraq has experienced increasing hydrological extremes, with intensified winter floods and prolonged summer droughts linked to seasonal variability in precipitation and temperature (Al-Ansari and Knutsson, 2011). The TaqTaq-Dokan Basin on the Little Zab River is particularly vulnerable. Major flood events in 1988 and 2019 illustrate this risk. In 2019, heavy rainfall in northern Iraq caused the Dokan reservoir to overflow, with the Little Zab River discharging approximately 1200 m³/s, or 103 million m³ per day. This excess runoff raised river levels by ~2 m and inundated extensive agricultural and residential areas downstream of the Dokan District (IMOS, 2025). Such events highlight the urgent need for reliable long-term forecasts of precipitation and runoff to support flood mitigation and water conservation planning. Accurate forecasting of rainfall and runoff is a central challenge in hydrology because rainfall generation involves multiple interacting, non-linear, and scale-

dependent physical processes (Dada et al., 2021). Traditional statistical methods such as linear regression and classical time-series models often fail to capture these complexities, especially under data-scarce and highly seasonal conditions. Early warning systems based on robust predictions can reduce fatalities, infrastructure damage, and agricultural losses, making predictive accuracy a critical priority for water resource management.

In response, artificial intelligence and, particularly, deep learning have emerged as powerful tools to extend traditional hydrological modelling. Unlike statistical models, deep learning architectures can learn non-linear relationships and temporal dependencies directly from data without strong a priori assumptions (Gelete et al., 2023). However, their application in data-limited basins requires careful justification. In this study we address three key methodological concerns: 1) Data sufficiency: We use 37 years of continuous monthly rainfall (1987–2024) from Koya Meteorological Station, which provides



444 monthly observations. This record length exceeds the minimum commonly recommended for training deep models in hydrology and allows a 70/30 train-test split while preserving inter-annual variability. 2) Model complexity and overfitting control: We compare five architectures of increasing complexity: MLP, CNN, RNN, LSTM, and GRU. Model selection is based not only on error metrics (MSE, RMSE, MAE) but also on information criteria (AIC, BIC) that penalize excess parameters, thereby guarding against overfitting. 3) Generalization and benchmarking: To demonstrate the added value of deep learning under limited data, all models are benchmarked against the SCS-CN method for runoff and against the performance of simpler ML models reported in regional studies. This ensures that any improvement is attributable to architecture rather than data artefacts.

Recent studies in Iraq and neighbouring regions support the potential of AI for rainfall prediction but also reveal important gaps. Tahseen and Ali (2025) found ANN outperformed MLR, XGBoost, SVR, and RF for monthly rainfall in Erbil. Hamaamin (2025) reported ANN ($R^2=0.75$) and ANFIS ($R^2=0.72$) performed well for daily precipitation in Sulaymaniyah. Muhamad and Ali (2025) showed ANN superior to MLR, ANFIS, LASSO, and ELNET in Pirmam, while Latif, Mohammed and Jaafar (2024) found a SARIMA-ANN hybrid outperformed standalone ANN in Sulaymaniyah. In southern Iraq, Alqahtani et al. (2023) demonstrated that a hybrid CNN-BDLSTM gave the best results for the Hawizeh, Hammar, and Central Marshes. Internationally, Aizansi, Ogunjobi and Ogou (2024) and Chen et al. (2022) reported mixed results favoring MLP and LSTM respectively, depending on climate and data length.

Despite this growing body of work, two critical gaps remain. First, most Iraqi studies focus on Erbil, Sulaymaniyah, or southern wetlands. No study to date has developed and validated a deep learning rainfall-runoff forecasting framework specifically for the TaqTaq-

Dokan Basin, a transboundary sub-basin with high flood risk and strategic importance for Dokan Dam operations. Second, prior work rarely addresses model parsimony and generalization under limited data, often applying complex models without comparison to simpler baselines or without reporting overfitting controls. To address these gaps, the present study applies and evaluates five deep learning architectures: MLP, CNN, RNN, LSTM, and GRU, to forecast monthly precipitation and estimate surface runoff in the TaqTaq-Dokan Basin up to 2030. By coupling data-driven precipitation forecasts with the SCS-CN runoff method and by explicitly testing for overfitting and generalization, this research provides a reproducible and operationally relevant tool for long-term water resource and agricultural planning in northern Iraq.

2. Material and Methods

2.1. Study Area

TaqTaq Dokan River Basin is located on the Little Zab River in Southeastern Erbil and has a large area of approximately 978 km². Moreover, the basin has a geographical coordinate that extends from 35°52'24.01"N 44°32'03.34"E in the downstream part and ends at 35°56'04.02"N 44°57'46.93"E in the upstream part of the basin, which is known as Kalkasmaq Mountain, which separates Erbil from Sulaimani Province, as shown in Figures 1 and 2. The area has average annual precipitation (614 mm), which starts in October and ends in June the next year. Based on the obtained data from the Iraqi Meteorological Organization and Seismology (IMOS), Koya Meteorological Station for the period (1987-2024), the maximum amount of monthly precipitation has been observed in January (127.5 mm), followed by December, March, February, November, April, October and May, with no rainfall in June, July, August and September, as presented in Figure 3.

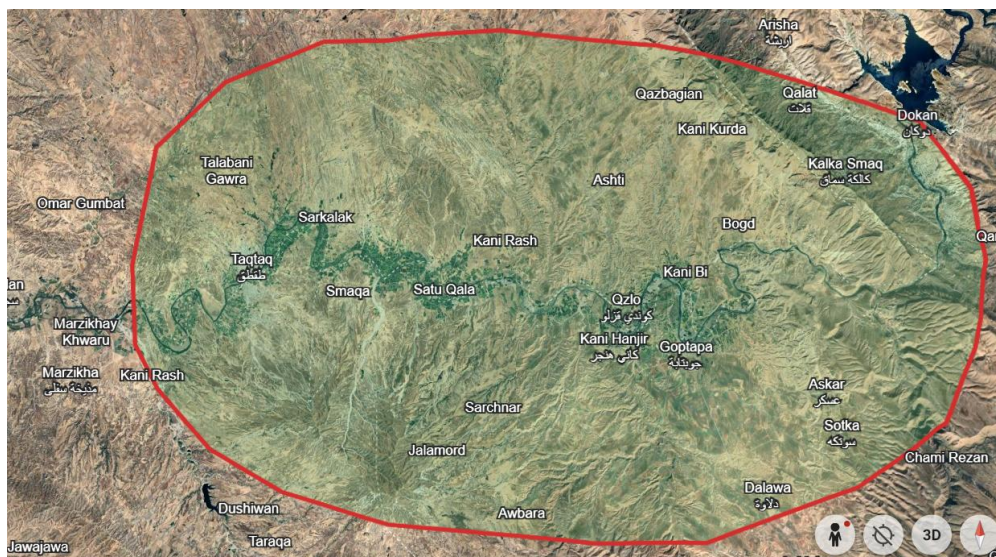


Figure 1. Taq-Taq Dokan drainage basin area and location of the proposed dam in Sarkalak (IMOS, 2025).

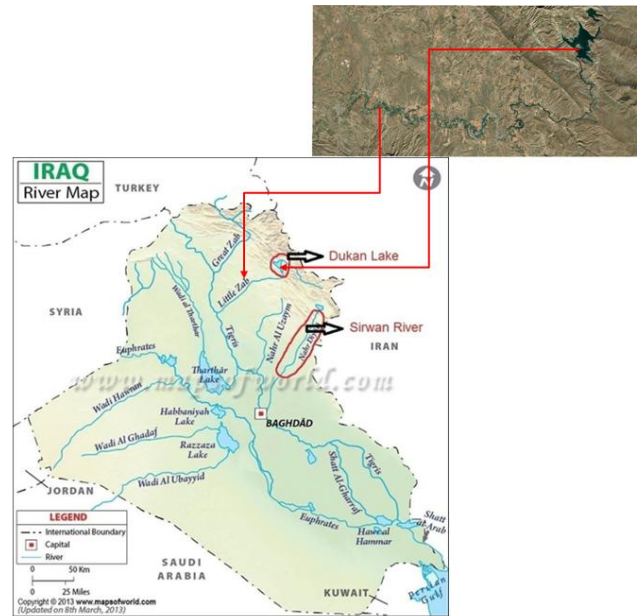


Figure 2. Location of TaqTaq-Dokan River Basin (Ali and Abdullah, 2019).

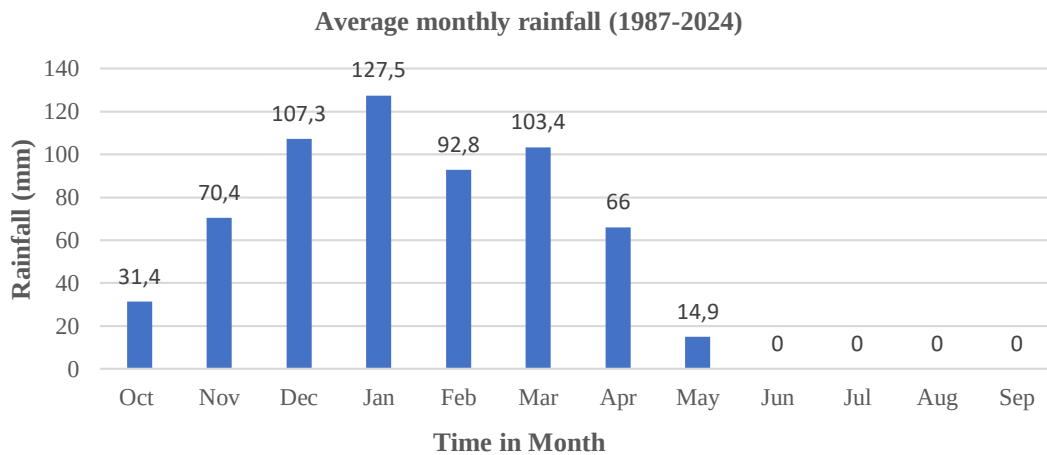


Figure 3. Average monthly rainfall in the Taq-Taq Dokan River Basin during 1987-2024 (IMOS, 2025).

2.2. Rainfall Data

The meteorological data have been obtained from the Iraqi Meteorological Organization and Seismology (IMOS), Koya Meteorological Station, for the period (1987-1988 to 2023-2024) as given in Table 1. Additionally, because of the climatic effects on most hydrologic phenomena, a water year or hydrologic year was adopted instead of a calendar year. The U.S. Geological Survey (USGS) has adopted the 12 months from 1st October to 30th September as the hydrologic year for the United States (Davis, 2010). This period was chosen for two reasons:

1. To break the record during the low-water period near the end of the summer season, and
2. To avoid breaking the record during the winter and to eliminate computation difficulties during the ice period (Davis, 2010).

As illustrated above, there are two missing data points for the hydrologic periods of 1990-1991 and 1991-1992 due to political instability in northern Iraq and the

consequences of the war between Iraq and Kuwait. For finding out the missing rainfall data during 1990 to 1992, a climatology forecast (CF) interpolation method has been applied to determine the average monthly rainfall for the aforementioned missing hydrologic years. Moreover, the CF model was applied twice to get better precision. Firstly, the average monthly rainfall was found for 1990-1991, and then the average of 35 years was utilized to determine the monthly amount of precipitation for 1991-1992. For determining the average monthly rainfall, the following Equation 1 was applied, which was stated mathematically as follows:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad (1)$$

where:

$\bar{x}$ is the climatological average monthly rainfall

n denotes the total number of observations in the historical data (36 observations),

x_i represents each observation. After inputting the monthly data for the whole duration, the average monthly amount of precipitation was obtained for the study area, as presented in Table 1.

2.3. Calculating the Surface Runoff Volume

Runoff is the rainwater that runs or flows over the natural land surface after water losses by interception, infiltration, and evaporation. It's the principal parameter and plays an important key role in the water budget. The simple and widely used Soil Conservation Service (SCS)-Curve Number (CN) method was used to estimate an approximately realistic value of total runoff from total rainfall in the study area (Jalal and Al-Kubaisi, 2024).

$$Q = \left(\frac{P - 0.2S}{P + 0.8S} \right)^2 \quad P > 0.2S \quad (2)$$

$$Q = 0 \quad P < 0.2S \quad (3)$$

where: Q = Runoff depth in (mm), P = Precipitation (monthly average of rainfall) in (mm), and S = Potential maximum retention after runoff begins, including initial abstraction which is assumed to be (0.2 S). Moreover, (S): related to soil and cover conditions, of the watershed

throughout CN, where CN denotes a range between (0 and 100), and (S) is related to (CN).

$$S = \frac{25400}{CN} - 254 \quad (4)$$

It can be observed that there are different land use types with diversified area percentage; therefore, in order to have a precise CN-value, the average Curve Number has been considered and it has been computed based on the equation (Equation 4). Based on this criterion, the following equation has been applied to determine the average value of CN for the whole basin area.

$$CN_{avg} = \frac{\sum(CNi \times Ai)}{\sum Ai} \quad (5)$$

$$Q \text{ volume} = Q \text{ depth} \times \text{Area} \quad (6)$$

where:

CNi: The Curve Number for a specific land use/soil group sub-area.

Ai: The area of that specific sub-area.

$\sum Ai$: The total area of the watershed.

Table 1. Total annual precipitation for the period 1991-2021 of the study area (IMOS, 2025)

Year	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Total
1987-1988	128.8	39.5	388.1	192.5	113.5	228.1	77.2	12.6	0	0	0	0	1180
1988-1989	3.1	19.6	221.9	25.3	41.1	102.7	0	0	0	0	0	0	413.7
1989-1990	11.6	274.7	110.1	117.9	129.1	26.9	125	0	0	0	0	0	795.3
1990-1991	29.8	66.7	101.5	120.7	87.8	97.9	62.4	14.1	0	0	0	0	580.9
1991-1992	30.6	68.5	104.4	124.1	90.2	100.6	64.2	14.5	0	0	0	0	597
1992-1993	0	0	90.5	82	90	101	316.5	69	0	0	0	0	749
1993-1994	185.2	182	78.5	181.1	101	122	78	8	0	0	0	0	935.8
1995-1996	0	15	37.8	225.3	50.8	272.9	77.2	12.3	0	0	0	0	691.3
1996-1997	1.8	7.2	112.3	110	205.5	155	0	0	0	0	0	0	591.8
1997-1998	16.5	95.2	131.2	221.3	102.7	214.6	56.2	16.8	0	0	0	0	854.5
1998-1999	5.5	23.8	5.3	127.6	113.4	5.9	26	0	0	0	0	0	307.5
1999-2000	14	17	91	174.3	41.1	36	15.4	2.5	0	0	0	0	391.3
2000-2001	12.5	15	132.5	60.2	85.4	131.5	26.2	15	0	0	0	0	478.3
2001-2002	9.3	36.3	161.7	230.5	38.5	139.5	52.5	6	0	0	0	0	674.3
2002-2003	2.1	86.6	256.8	172.5	103	184.3	40.5	12.5	0	0	0	0	858.3
2003-2004	11.8	142.7	168	335.5	123	25.5	129.3	12	0	0	0	0	947.8
2004-2005	0	206.5	17	167	169	74	47	1	0	0	0	0	681.5
2005-2006	0	17	39.5	169.8	103.1	7	103.5	36.5	0	0	0	0	476.4
2006-2007	171.5	41	28	81	159.1	75.8	100.4	41.8	0	0	0	0	698.6
2007-2008	0	5.5	13	76.5	57.6	63.5	1.5	0	0	0	0	0	217.6
2008-2009	61.5	11	28	1.5	41.5	72	59.5	0.5	0	0	0	6	281.5
2009-2010	66	33.5	160.5	42.1	145.5	123	66	21	5	0	0	0	662.6
2010-2011	5.5	0	38	158	60.3	49	149	22.5	5	0	0	0	487.3
2011-2012	12.5	14.5	46.5	158.3	76	122.2	36	8	0	0	0	0	474
2012-2013	18	51	135.3	254.5	95.7	10.9	10.6	16.4	0	0	0	0	592.4
2013-2014	0	69.5	117.7	69.5	7.6	141	30.3	3.9	0	0	0	0	439.5
2014-2015	87.2	151.8	78	51.2	43.3	82.4	25.9	12.5	0	0	0	21	552.9
2015-2016	110.1	186.7	78.2	100	49	165.5	84	0	0	0	0	0	773.5
2016-2017	2	26	170.5	47	34.9	102.2	51.2	8.5	0	0	0	0	442.3
2017-2018	0	65.4	25.1	55.4	299.7	21.7	73.4	46.8	0	0	0	0	587.5
2018-2019	46	195	323	132.5	94	227.4	176.8	25.5	0	0	0	0	1220
2019-2020	69.5	58.5	75.7	137.3	86.2	165.5	43.2	23	3	0	0	0	661.9
2020-2021	0	39.8	42.5	49.8	66.8	24.3	9.6	4.3	0	0	0	0	237.1
2021-2022	4.5	4.6	113.4	132.6	42.5	35.1	10.2	25.3	0	0	0	0	368.2
2022-2023	7.9	122	42	105.6	45.1	131.2	73.2	10.4	0	0	0	0	537.4
2023-2024	7	145.8	98	101.1	146.1	84.6	76.5	32	0	0	0	5	696.1
Average	31.4	70.4	107.3	127.5	92.8	103.4	66.0	14.9	0.4	0.0	0.0	0.9	614.9

2.4. Digital Elevation Model (DEM)

The WMS 11.1 (Watershed Modeling System version 11.1) is selected as the hydrological Model to simulate the TaqTaq Dokan River catchment for the feasibility study (Figure 4). A study of this nature needs a model that takes into account as many catchment characteristics as possible (land use, soil information, temperature data, and rainfall data, etc.).

The DEM has changed to Triangulated Irregular Network (TIN) in order to define the three-dimensional surface area of the Basin which has been presented in the Table 2.

2.5. Computation of the Curve Number (CN)

The CN is one of the essential and most important variables in the estimation of runoff, a higher CN indicates higher runoff. In the current study the relevant CN number was selected as a function of land use land cover (LULC) as given in Figure 5 and Table 3. Moreover, the AMC II (Antecedent Moisture Condition type II) curve number was chosen for the calculation of daily runoff data. Many samples were taken from the watershed area and tested in the College of Engineering Soil Lab in order

to classify them. The results were illustrated in Table 4. The table shows that the classification of the soil type ranges from Sandy clay (A), Loam (B), Sandy clay loam (C) and Clay and Clay Loam (D) (Withers and Vipond, 1974). For this reason, the average hydrologic soil condition curve number has been used in the calculation. From many investigations for the study area, the area of the catchment has been divided based on the Land Use map extracted from the Google Earth Engine, as revealed in Table 3.

1. A percentage area of about (60%) of non-cultivated agricultural land, pasture with no mechanical treatment practice and medium hydrological condition, the CN is ranging from 82 to 89.
2. A percentage area of about (33%) of non-cultivated agricultural land, pasture with No mechanical treatment practice and medium to good hydrological conditions. (CN=72, 81, 88, 91)

A very small percentage area about 7%) of grassland, shrubs, forests, built-up area and water bodies compose the basin area with low, medium and good hydrological conditions (CN varies from 39 to 100).

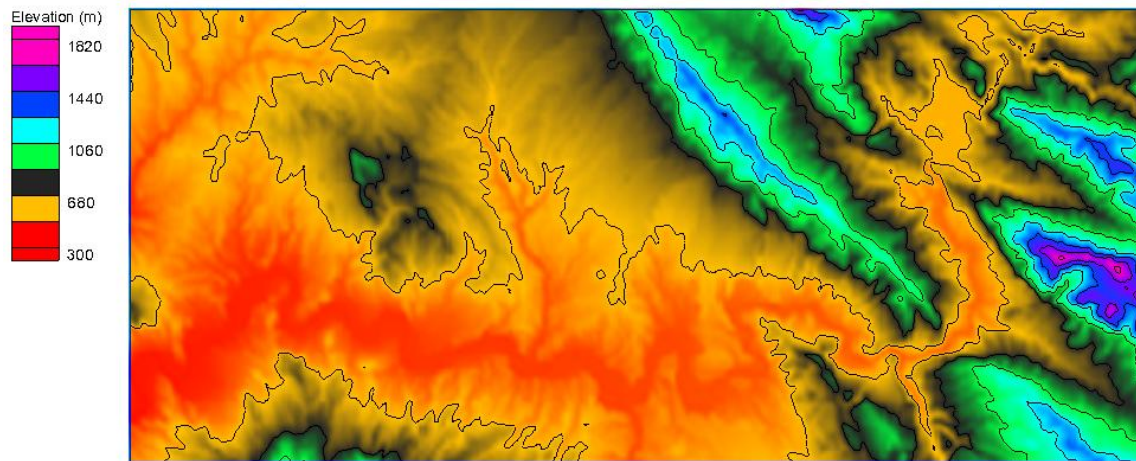


Figure 4. Digital elevation model (DEM) of TaqTaq Dokan River basin.

Table 2. General properties of the TIN extracted from the Watershed Modelling System (WMS 11.1)

Property	Value	Unit
TIN ID	24141	-
Number of Vertices	74847	-
Number of Triangles	148512	-
Max z	1671.99	m
Min z	313.5	m
TIN Area	977.9082	km ²
Centroid, x	482193.44	m
Centroid, y	3975463.61	m
Centroid, z	586.78	m

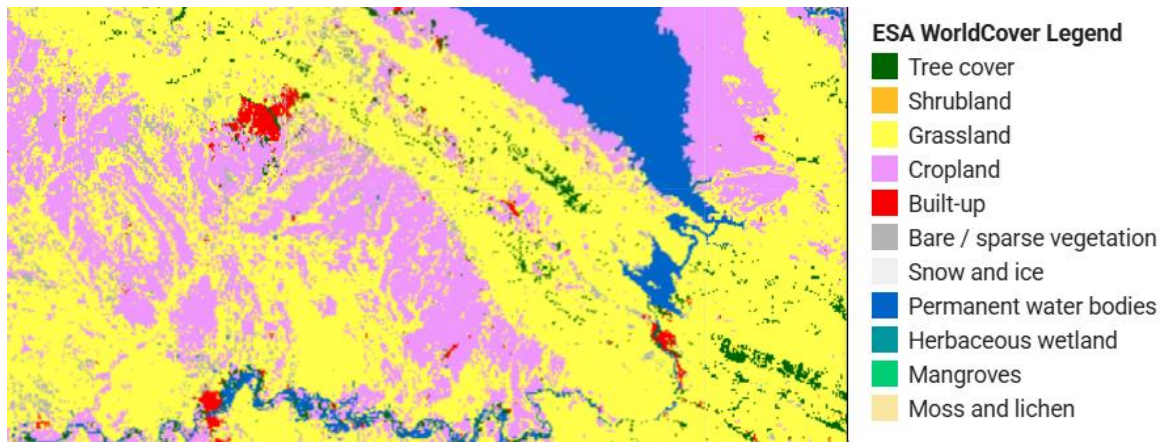


Figure 5. Land use cover for the study area. Source: Google Earth Engine, 2026.

Table 3. Classification of different land use types, curve number (CN) and area of specific sub-area in the study area

Land Use Type	Texture	HSG	CNi	Ai	CNi × Ai
Bare	Clay	D	89	160	14240
Bare	Clay loam	D	89	370	32930
Bare	Loam	B	82	2	164
Built-up	Clay	D	98	10	980
Built-up	Clay loam	D	98	20	1960
Cultivation	Clay	D	91	140	12740
Cultivation	Clay loam	D	91	115	10465
Cultivation	Loam	B	81	32	2592
Cultivation	Sandy clay	A	72	3	216
Cultivation	Sandy clay loam	C	88	7	616
Forest	Clay	D	83	1	83
Forest	Clay loam	D	83	1	83
Forest	Sandy clay loam	C	77	1	77
Grass	Clay	D	80	7	560
Grass	Clay loam	D	80	8	640
Grass	Sandy clay	A	39	15	585
Shrub	Clay	D	89	1	89
Shrub	Clay loam	D	89	1	89
Shrub	Loam	B	79	12	948
Shrub	Sandy clay	A	68	1	68
Shrub	Sandy clay loam	C	86	1	86
Water	Clay	D	100	25	2500
Water	Clay loam	D	100	45	4500
CN-avge = 89 for the whole basin				$\sum Ai = 978$	$\sum (Cni \times Ai) = 87211$

2.6. Statistical Parameters

Five deep learning techniques have been applied to forecast the annual precipitation and runoff in the study area, including Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long-Short Term Memory (LSTM) and Gated Recurrent Unit (GRU). The data set has been split into training (70%) and testing (30%). Moreover, the efficiency of each model has been evaluated through five different statistical performance parameters, including Mean Square Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

3. Results

3.1. Summary Interpretation of Model Performance, Hydrology, and Forecasting

The statistical evaluation of five deep learning architectures showed that RNN achieved the highest forecasting accuracy for monthly precipitation in the TaqTaq-Dokan Basin, with MSE = 1009.65, RMSE = 31.78, and MAE = 23.09 (Table 9). The model ranking was RNN > CNN > LSTM > GRU > MLP. The superior performance of the simple RNN over LSTM and GRU can be explained by the characteristics of the dataset and the basin's hydrology. The TaqTaq-Dokan rainfall record exhibits strong, regular annual seasonality with a short memory: high winter rainfall followed by four consecutive dry

months. In such conditions, complex gating mechanisms in LSTM and GRU are not required and can lead to over-parameterisation. The RNN with only one hidden layer and 12 neurons had the lowest AIC (797.79) and BIC (1185.70), indicating better parsimony and generalisation under limited data (37 years). In contrast, LSTM and GRU required 2-4x more parameters, resulting in higher AIC/BIC and slightly higher MAE, suggesting a tendency toward overfitting. CNN performed second best because convolutional filters effectively captured local temporal patterns of the wet season but lacked the explicit recurrence needed for year-to-year dependency. MLP performed worst because feed-forward networks cannot model sequential dependencies directly.

Hydrologically, all models reproduced the basin's Mediterranean climate signature: concentrated rainfall from October to May with peaks in December–February, and zero rainfall/runoff from June to September (Table 10). The 2024–2030 forecast averages 538.5 mm yr⁻¹ of rainfall and generates ~331.37 million m³ yr⁻¹ of runoff, compared to 396.56 million m³ yr⁻¹ observed for 1987–2021 (Table 11, Table 12). The 16.4% decrease in forecasted runoff is driven by lower predicted winter peaks, particularly in January and February. Despite this decrease, the volume remains substantial. With CN = 89, steep slopes of 313.5–1671.99 m, and thin soils, the basin converts >70% of winter rainfall to surface runoff once the initial abstraction Ia = 0.2S is exceeded. This explains historical flood events in 1988 and 2019 when Little Zab discharge reached ~1200 m³/s. The high correlation between observed and predicted runoff (r=0.902, Figure 12) confirms that the models captured both the wet-season hydrograph and the summer zero-flow period.

Compared to similar studies in semi-arid and Mediterranean regions, these results are consistent but context-dependent. In Erbil and Pirmam, Tahseen and Ali (2025) and Muhamad and Ali (2025) also found ANN-type models outperformed statistical and tree-based models for monthly rainfall. In Benin (West Africa, sub-humid), Aizansi et al. (2024) reported MLP > LSTM, while in Turkey, Chen et al. (2022) found LSTM > RF. In the southern Iraq marshes, Alqahtani et al. (2023) found CNN-BDLSTM optimal. The variation across studies confirms that no single architecture is universally superior. In basins with short, highly seasonal records like TaqTaq-Dokan, a parsimonious RNN often generalizes better than deeper LSTM/GRU networks, as also observed here.

Regarding climate variability, the forecast indicates a shift toward slightly lower winter peaks but persistent summer drought. If this trend continues, two implications arise for runoff generation: 1) Reduced total annual runoff may decrease flood frequency but will not eliminate winter flood risk due to the high CN and rapid response. 2) Longer dry periods and zero summer runoff will increase water scarcity stress from June to September. Therefore, the ~331 million m³ yr⁻¹ of forecasted seasonal runoff represents a critical but

currently unregulated resource. While this study provides only preliminary hydrological evidence, these forecasts can serve as input for future multidisciplinary assessments that must also consider storage, sedimentation, geotechnical, environmental, and economic factors before any infrastructure decision.

In summary, the results demonstrate that a simple RNN architecture is most effective for forecasting seasonal precipitation in data-limited, Mediterranean basins. The models reliably capture seasonal dynamics and provide a 6-year outlook that can support planning for flood mitigation and water conservation, while acknowledging that climate variability may further alter the magnitude and timing of future runoff.

3.2. Statistical Evaluation of the Architectures

3.2.1. MLP

Table 4 presents the performance comparison of several Multi-Layer Perceptron (MLP) architectures using five evaluation metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). The results indicate clear variability in predictive performance across different hidden-layer structures. The architecture (48, 24) achieved the lowest MAE (24.707417), indicating superior predictive accuracy compared with other architectures. Although the architecture (8) recorded the smallest MSE (1127.663452) and RMSE (33.580701), its MAE values were higher than those of (48, 24), suggesting less consistent prediction performance. Additionally, AIC and BIC values increased with model complexity, with (48, 24) showing the largest values, which is expected due to the higher number of parameters. However, despite the penalty for complexity, the predictive accuracy of (48, 24) remained superior. Overall, considering MAE as the primary accuracy indicator for forecasting performance, the MLP architecture (48, 24) was selected as the most suitable model.

3.3. Deep Learning Multi-Architectures and Statistical Parameters

Moreover, as illustrated in Figure 6 above, the plot shows that architecture (48, 24) achieves the lowest prediction errors compared with other CNN structures. This confirms the superiority of a deeper convolutional architecture for capturing temporal patterns.

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3.3.1. CNN

Table 5 presents the comparison of different Convolutional Neural Network (CNN) architectures using 5 evaluation metrics, including MSE, RMSE, MAE, AIC, and BIC. The results demonstrate noticeable differences in prediction performance among the tested architectures. The architecture (24, 12) achieved the

lowest MSE (1017.615716) and RMSE (31.900090), indicating strong performance in minimizing squared prediction errors. However, the architecture (32, 16) produced the lowest MAE (23.731448), suggesting better overall forecasting accuracy and improved robustness against extreme values. Although the architecture (16, 8) also showed competitive performance with low MSE (1022.152558) and MAE (23.881005), its error values were slightly higher than those of (32, 16). Furthermore, AIC and BIC values increase with model complexity, and the architecture (32, 16) exhibits larger AIC and BIC values due to higher parameterization, which is expected

for deeper CNN structures. Overall, considering MAE as a primary indicator of predictive accuracy, the CNN architecture (32, 16) was selected as the most suitable model. This architecture provides improved prediction stability, better fitting of nonlinear patterns, and enhanced forecasting performance for precipitation time-series data.

Additionally, as can be observed from Figure 7, the plot shows that architecture (32, 16) achieves the lowest prediction errors compared with other CNN structures. This confirms the superiority of a deeper convolutional architecture for capturing temporal patterns.

Table 4. MLP architecture comparison

Architecture	MSE	RMSE	MAE	AIC	BIC
(8)	1127.663452	33.580701	25.015215	668.7579	910.9321
(12)	1218.910915	34.912905	25.423874	785.6599	1147.8497
(16, 8)	1215.552636	34.864776	25.053138	1153.4861	1910.0127
(20, 10)	1365.150853	36.947948	27.510682	1416.7983	2447.6461
(24, 12)	1390.121166	37.284329	26.493720	1705.9402	3045.3994
(32, 16)	1129.596071	33.609464	25.149468	2364.8658	4424.4182
(48, 24)	1188.918616	34.480699	24.707417	4096.0904	8007.3112

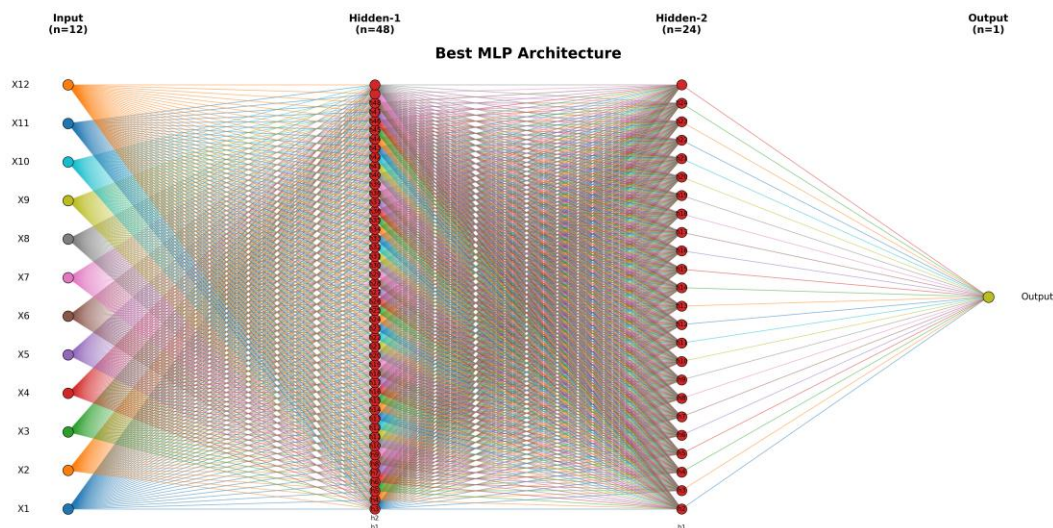


Figure 6. MLP best architecture plot.

Table 5. CNN architecture comparison.

Architecture	MSE	RMSE	MAE	AIC	BIC
(8)	1050.702875	32.414547	25.444865	5976.3045	11910.6446
(12)	1134.148519	33.677122	24.477425	8557.1192	17251.8167
(16, 8)	1022.152558	31.971121	23.881005	11382.5690	23111.9453
(20, 10)	1155.578137	33.993796	24.996735	14110.2984	28754.3380
(24, 12)	1017.615716	31.900090	24.464250	16854.2887	34447.2817
(32, 16)	1069.617714	32.705011	23.731448	22457.4286	46051.1988
(48, 24)	1094.431340	33.082191	24.565313	34042.8734	70049.6799

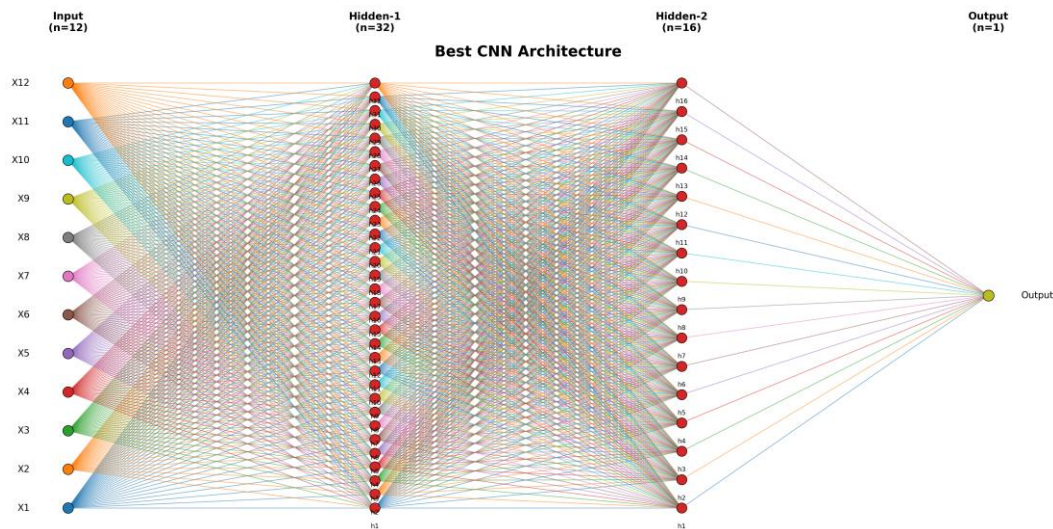


Figure 7. CNN best architecture plot.

3.3.2. RNN

Table 6 presents the performance comparison of different Recurrent Neural Network (RNN) architectures using evaluation metrics including MSE, RMSE, MAE, AIC, and BIC. The results indicate that the architecture (12) achieved the lowest MSE (1009.654576), RMSE (31.775062), and MAE (23.087294), demonstrating superior prediction accuracy compared with other architectures. Although architecture (32, 16) showed competitive MAE (24.136223) and lower MSE compared with several models, its performance remained inferior to (12). On the other hand, deeper architectures such as (16, 8), (20, 10), and (24, 12) exhibited higher error values, suggesting that increasing network complexity did not necessarily improve prediction performance for this dataset. Moreover, AIC and BIC values increased substantially with model complexity, indicating a higher penalty for larger architectures. Overall, based on the minimum error values and balanced performance across evaluation metrics, the RNN architecture (12) was selected as the most suitable model. This architecture provides better generalization ability and efficient learning of temporal dependencies in precipitation time-series data.

Furthermore, as presented in Figure 8, the plot indicates that architecture (12) achieves the lowest error values among all RNN structures. This confirms that a single hidden layer with 12 neurons is optimal for this dataset.

3.3.3. LSTM

Table 7 presents the performance comparison of different Long Short-Term Memory (LSTM) architectures using multiple evaluation metrics, including MSE, RMSE, MAE, AIC, and BIC. The results indicate that the architecture (20, 10) achieved the lowest MAE (23.576105), demonstrating superior forecasting accuracy compared with the other tested architectures. Although the architecture (12) recorded slightly lower MSE (1048.624301) and RMSE (32.382469), its MAE values were higher than those of (20, 10), suggesting less accurate overall predictions. Similarly, the architecture

(8) showed competitive performance but remained inferior to (20, 10) across most evaluation criteria. More complex architectures such as (32, 16) and (48, 24) exhibited higher error values, indicating that excessive model complexity did not improve predictive performance for this dataset. Additionally, AIC and BIC values increased with model size, reflecting the penalty for increased model parameters. Overall, based on the lowest MAE and RMSE values and balanced predictive performance, the LSTM architecture (20, 10) was selected as the most suitable model. This architecture effectively captures long-term temporal dependencies in precipitation data and provides improved forecasting accuracy.

Moreover, as highlighted in Figure 9, the plot shows that architecture (20, 10) achieves the minimum prediction error among the tested LSTM models. This confirms that a two-layer LSTM structure improves learning performance.

3.3.4. GRU

Table 8 presents the performance comparison of different Gated Recurrent Unit (GRU) architectures using evaluation metrics including MSE, RMSE, MAE, AIC, and BIC. The results indicate that the architecture (48, 24) achieved the lowest MAE (24.140111), demonstrating superior forecasting accuracy compared with other GRU structures. Although the architecture (8) recorded relatively lower MSE (1115.121502) and RMSE (33.393435), its MAE values were higher than those of (48, 24), indicating less accurate predictions. The architecture (32, 16) also showed competitive performance with MAE (24.374528), but its error values remained slightly higher than the selected model. In contrast, deeper configurations such as (16, 8) and (20, 10) exhibited substantially larger error values, suggesting that these architectures overfit or failed to capture temporal dependencies effectively. Additionally, AIC and BIC values increased with network complexity, which reflects the penalty for additional parameters in larger GRU models. Overall, considering MAE as the

primary indicator of forecasting accuracy, the GRU architecture (48, 24) was selected as the most suitable model. This architecture provides improved learning of

temporal dependencies and better generalization performance for precipitation forecasting.

Table 6. RNN architecture comparison

Architecture	MSE	RMSE	MAE	AIC	BIC
(8)	1087.403401	32.975800	25.088756	618.4675	809.2065
(12)	1009.654576	31.775062	23.087294	797.7939	1185.7013
(16, 8)	1288.442537	35.894882	26.719621	1317.1549	2245.1323
(20, 10)	1216.832315	34.883124	26.212149	1769.5524	3186.1645
(24, 12)	1143.649083	33.817881	26.341683	2317.6447	4325.7619
(32, 16)	1075.183918	32.789997	24.136223	3705.7556	7205.4946
(48, 24)	1137.374784	33.724988	24.158032	7645.2981	15362.7263

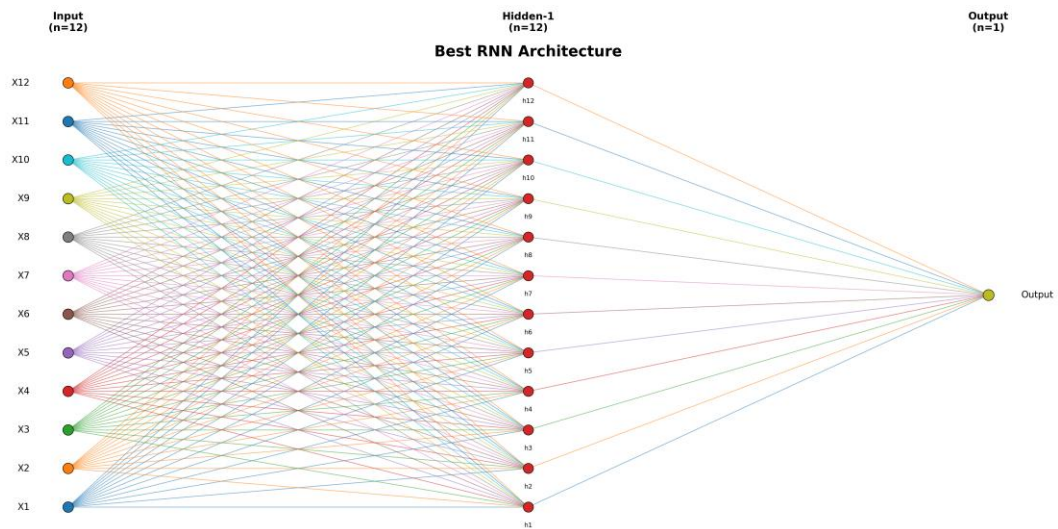


Figure 8. RNN Best Architecture Plot.

Table 7. LSTM architecture comparison

Architecture	MSE	RMSE	MAE	AIC	BIC
(8)	1060.859888	32.570844	24.697693	1096.9106	1802.0019
(12)	1048.624301	32.382469	24.251647	1808.1798	3276.2271
(16, 8)	1086.868030	32.967682	24.480828	3034.4365	5814.0822
(20, 10)	1105.792297	33.253455	23.576105	4403.5240	8649.0739
(24, 12)	1119.323965	33.456299	24.315975	6060.2903	12080.3557
(32, 16)	1191.047341	34.511554	24.940039	10240.2031	20735.1338
(48, 24)	1162.946330	34.101999	25.107427	22046.6989	45194.6970

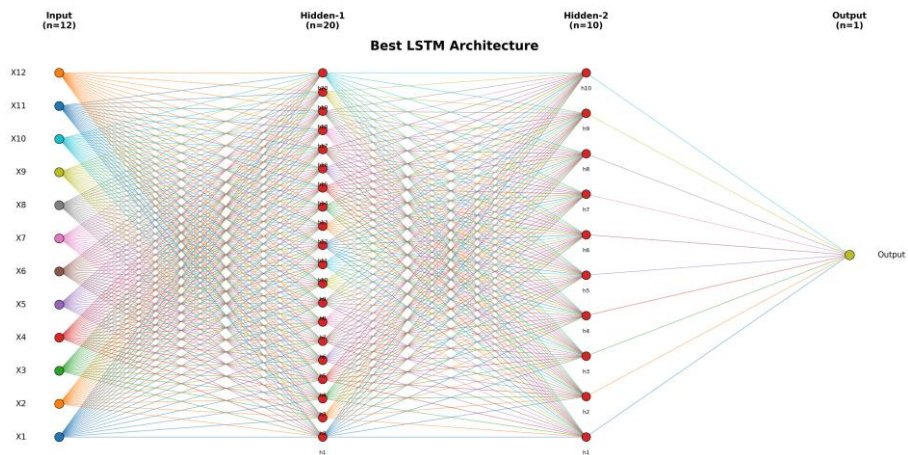


Figure 9. LSTM best architecture plot.

Finally, as demonstrated from the Figure 10, the plot shows that architecture (48, 24) achieves the lowest prediction errors among GRU models. This confirms the advantage of a deeper GRU structure for capturing rainfall patterns.

3.4. Final Summary of the Models' Optimum Architecture

Table 9 presents the comparison of the best architectures for five deep learning methods, including MLP, CNN, RNN, LSTM, and GRU, using evaluation metrics such as MSE, RMSE, MAE, AIC, and BIC. The results indicate that the RNN model with architecture (12) achieved the lowest MSE (1009.654576), RMSE (31.775062), and MAE (23.087294), demonstrating the highest prediction accuracy among all methods. The CNN model with architecture (32, 16) ranked second, producing competitive error values (MSE=1069.617714, MAE=23.731448), followed by the LSTM model (20, 10), which achieved similar MAE (23.576105). The GRU model (48, 24) showed moderate performance with slightly higher error values, whereas the MLP model (48, 24) recorded comparatively larger RMSE and weaker overall accuracy. Overall, based on the combined evaluation metrics, the models can be ranked according to forecasting performance as follows: RNN (12) ranked first, CNN (32, 16) ranked second, LSTM (20, 10) ranked third, GRU (48, 24) ranked fourth, and MLP (48, 24) ranked last. These findings indicate that recurrent-based models, particularly the RNN architecture, provide better capability for capturing temporal dependencies in precipitation time-series data and yield more accurate forecasting results.

3.5. Results of Predicting Precipitation by different ANN Models (2025-2030)

Table 10 presents the 72-month forecast of monthly precipitation using MLP, CNN, RNN, LSTM, and GRU models for the period October 2024 to September 2030. The results clearly demonstrate a consistent seasonal rainfall pattern across all models. For example, in October 2024, predicted rainfall ranges from 5.18 mm (MLP) to 29.17 mm (CNN), while in November 2024, values increase to between 41.75 mm (MLP) and 65.13 mm (RNN). The precipitation reaches peak values during winter months, particularly in January 2025, where predictions vary from 96.93 mm (CNN) to 130.20 mm (MLP), and February 2025, ranging between 99.30 mm (CNN) and 120.51 mm (MLP). The rainfall then gradually decreases in March 2025 (74.06–99.76 mm) and April 2025 (53.93–84.14 mm), followed by low rainfall in May 2025 (23.91–34.69 mm), while all models predict zero rainfall from June to September, reflecting the dry summer season. This seasonal pattern is repeated throughout the forecast horizon. For instance, in January 2028, rainfall predictions range between 72.16 mm (CNN) and 130.72 mm (MLP), and in February 2029, forecasts vary from 76.57 mm (CNN) to 129.95 mm (MLP). Similarly, in January 2030, predicted precipitation ranges from 69.63 mm (CNN) to 124.26 mm (MLP). These consistent peaks during the winter months and

zero rainfall during the summer months confirm that all models successfully captured the periodic hydrological behavior of precipitation. Overall, the forecasted results show strong agreement among models, with the RNN and LSTM models producing smoother transitions, while MLP predicts higher winter peaks, and CNN provides comparatively moderate estimates. The similarity of predicted values across models and across forecasted years indicates stable and reliable long-term precipitation forecasting.

3.6. Observed Annual Runoff

Based on the methodology, the annual volume of runoff has been estimated using equations 2, 3, 4 and 5 for the last 37 year (1987-2024) in the study area, as demonstrated in Table 11. It can be seen that the maximum monthly runoff has happened in January due to high amount of precipitation, whereas, despite of having a small amount of rainfall from June to September, the volume of runoff is zero because the rainfall amount in summer periods is generally smaller than the initial abstraction value (0.2S) based on Equations 2 to 5 highlighted from the methodology sections. Therefore, over the last 37 years, more specifically from 1991 to 2021, there has been a large amount of water discharged into the river and valleys without getting any benefits from it. Additionally, in high rainfall seasons, the surface water runoff has resulted in flooding and destroyed tens of thousands of acres of agricultural lands, residential areas and fish ponds in the region, as it happened more recently in 2019.

3.7. Predicted Amount of Annual Runoff in TaqTaq Dokan Basin

As illustrated in Table 12, the predicted amount of runoff varies over the hydrologic year and based on the previous methodologies, the surface runoff is correlated with the amount of precipitated rain in the area. The surface runoff due to high potential precipitation starts from October and ends in May next year, in which the peak runoff will occur in January, amounting to approximately 77 million m³ as revealed in the (Table 12). Moreover, for the other months, the runoff is gradually declining due to the decrease in rainfall in the area. There will be no runoff in the summer period, as presented in the table 12. Therefore, there will be a fair amount of surface runoff from October to the end of May which is slightly more than 331 million m³ for each year for the period of 2025 to 2030 (72 months forecast). Consequently, regardless of evaporation and infiltration of water to the underground, a large amount of surface water is discharging to the Dokan River (Little Zab River) without getting any benefit to the agriculture, drinking water supply and hydropower. Finally, as it has been illustrated from the Figure 12, there is a high correlation between the observed and predicted volume of runoff ($r=0.902$), the prediction model successfully captures the overall hydrograph schematics and the dry season zero flow periods, however the model slightly underpredicts peak discharge volumes from October to January as presented in Figure 12.

Table 8. GRU architecture comparison

Architecture	MSE	RMSE	MAE	AIC	BIC
(8)	1115.121502	33.393435	26.388473	988.0533	1573.1291
(12)	1140.152731	33.766148	26.981616	1549.4518	2734.6053
(16, 8)	1329.365055	36.460459	28.866641	2567.1248	4832.4182
(20, 10)	1293.595905	35.966594	28.417130	3653.4064	7084.5651
(24, 12)	1215.851681	34.869065	24.911312	4961.5016	9798.5567
(32, 16)	1130.117982	33.617227	24.374528	8252.8949	16621.8360
(48, 24)	1244.082184	35.271549	24.140111	17538.9477	35852.0339

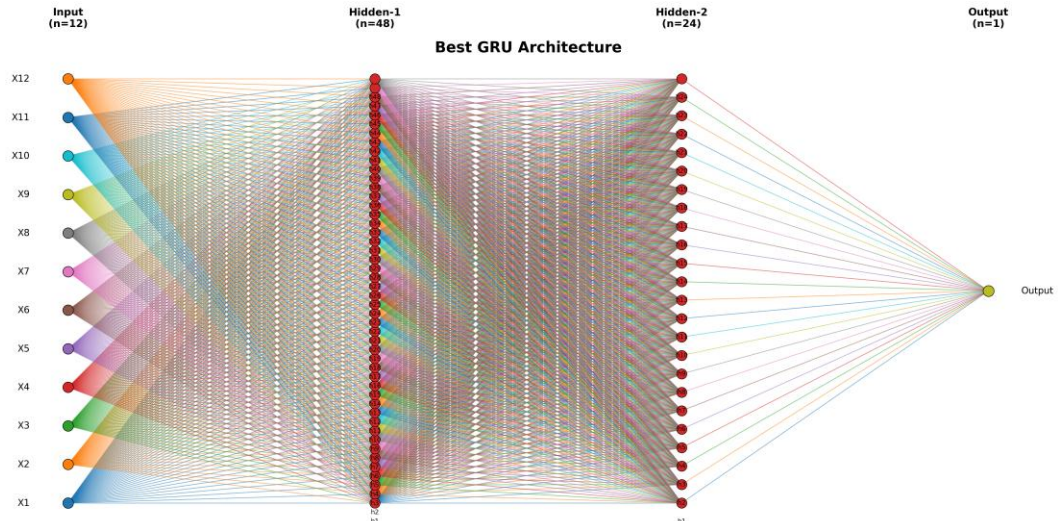


Figure 10. GRU best architecture plot.

Table 9. Final summary: best architectures per method

Method	Best Architecture	MSE	RMSE	MAE	AIC	BIC
MLP	(48, 24)	1188.9186	34.480699	24.707417	4096.0904	8007.3112
CNN	(32, 16)	1069.6177	32.705011	23.731448	22457.429	46051.199
RNN	(12)	1009.6546	31.775062	23.087294	797.7939	1185.7013
LSTM	(20, 10)	1105.7923	33.253455	23.576105	4403.524	8649.0739
GRU	(48, 24)	1244.0822	35.271549	24.140111	17538.948	35852.034

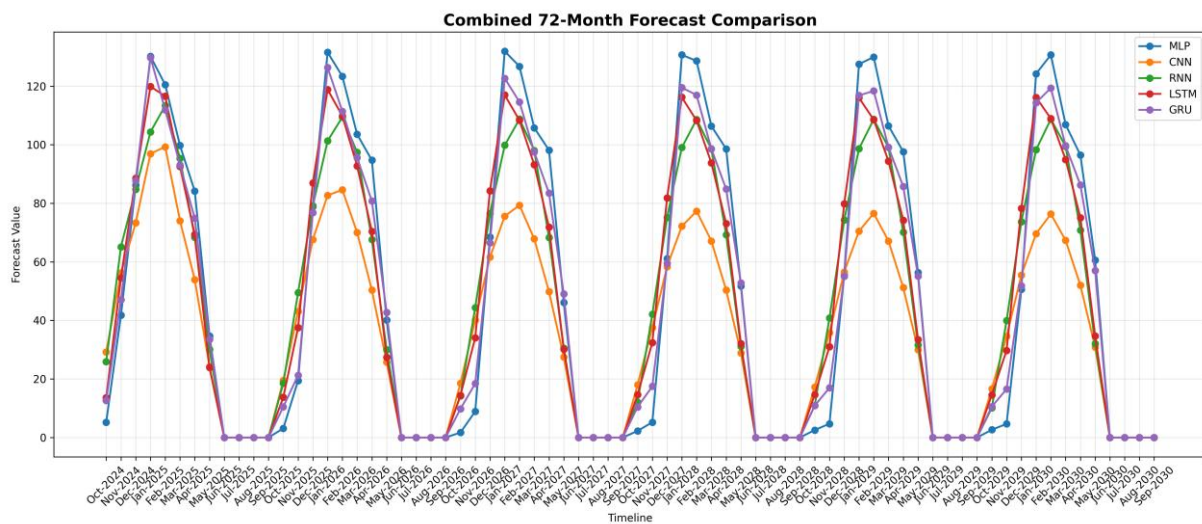


Figure 11. Combined forecast comparison plot of MLP, CNN, RNN, LSTM and GRU.

Table 10. Precipitation forecast until 2030 by different ANN models

Years	Models	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
2024-2025	MLP	5.175	41.754	86.256	130.204	120.506	99.755	84.141	34.688
	CNN	29.173	56.229	73.354	96.933	99.298	74.055	53.927	24.218
	RNN	25.914	65.125	84.798	104.369	113.352	95.324	68.385	30.059
	LSTM	13.593	54.551	88.585	119.909	116.553	92.573	69.306	23.909
	GRU	12.635	47.026	87.749	129.758	111.906	93.074	74.859	33.58
2025-2026	MLP	3.111	19.444	78.868	131.575	123.356	103.568	94.708	40.092
	CNN	19.493	43.1	67.599	82.71	84.591	70.047	50.334	25.729
	RNN	18.552	49.513	79.151	101.331	109.428	97.436	67.581	29.996
	LSTM	13.786	37.546	86.966	118.857	109.822	92.78	70.347	27.419
	GRU	10.464	21.249	76.831	126.39	111.402	95.573	80.754	42.748
2026-2027	MLP	1.695	8.879	68.456	131.934	126.775	105.786	98.148	46.096
	CNN	18.524	40.099	61.59	75.59	79.334	67.861	49.829	27.439
	RNN	14.211	44.368	76.567	99.823	108.758	98.062	68.288	30.509
	LSTM	14.376	34.037	84.298	117.01	108.317	93.179	71.827	30.122
	GRU	9.773	18.409	66.475	122.698	114.619	97.554	83.481	49.036
2027-2028	MLP	2.238	5.208	61.085	130.716	128.615	106.403	98.585	51.75
	CNN	17.982	37.542	58.33	72.162	77.329	67.119	50.387	28.888
	RNN	12.058	42.089	75.174	99.067	108.65	98.583	69.25	31.099
	LSTM	14.604	32.385	81.852	116.207	108.237	93.781	73.104	32.023
	GRU	10.425	17.458	59.483	119.518	116.973	98.614	84.878	52.805
2028-2029	MLP	2.533	4.706	55.547	127.547	129.954	106.448	97.618	56.304
	CNN	17.255	35.81	56.514	70.486	76.573	67.109	51.198	30.02
	RNN	10.88	40.796	74.286	98.624	108.681	99.054	70.116	31.627
	LSTM	14.638	30.996	79.871	116.063	108.541	94.388	74.178	33.491
	GRU	10.875	16.96	55.008	116.837	118.4	99.173	85.699	55.165
2029-2030	MLP	2.634	4.66	50.627	124.26	130.692	106.878	96.484	60.548
	CNN	16.605	34.568	55.429	69.625	76.337	67.324	51.965	30.854
	RNN	10.133	39.93	73.657	98.328	108.742	99.448	70.821	32.064
	LSTM	14.592	29.752	78.273	116.197	108.928	94.944	75.09	34.685
	GRU	10.552	16.52	51.838	114.373	119.383	99.646	86.272	56.992
Average monthly		12.61597	32.35697	71.15057	109.3034	108.8017	92.51797	74.052	37.13183

Table 11. Observed annual surface runoff in Taq-Taq Dokan Basin Area for the period 1991-2021

Month	Average Monthly Rainfall (mm)	CN	S	0.2S	Q (mm)	Area (Km ²)	Volume (m ³)
Oct	31.44	89	31.4	6.3	11.19	978	10948098
Nov	70.4	89	31.4	6.3	43.05	978	42099250
Dec	107.3	89	31.4	6.3	77.07	978	75375339
Jan	127.5	89	31.4	6.3	96.29	978	94167485
Feb	92.8	89	31.4	6.3	63.49	978	62089449
Mar	103.4	89	31.4	6.3	73.40	978	71782035
Apr	66	89	31.4	6.3	39.14	978	38283361
May	14.9	89	31.4	6.3	1.86	978	1816648
Jun	0.4	89	31.4	6.3	0	978	0
Jul	0	89	31.4	6.3	0	978	0
Aug	0	89	31.4	6.3	0	978	0
Sep	0.9	89	31.4	6.3	0	978	0
Average Annual Runoff (1987-2021)							396561666

Table 12. Predicted amount of annual runoff in the TaqTaq Dokan basin

Month	Average Monthly Rainfall (mm)	CN	S	Ia=0.2S	Q (mm)	Area (Km ²)	Volume (m ³)
Oct	12.6	89.0	31.4	6.3	1.1	978	1036212.2
Nov	32.4	89.0	31.4	6.3	11.8	978	11568189.6
Dec	71.2	89.0	31.4	6.3	43.7	978	42754129.0
Jan	109.3	89.0	31.4	6.3	79.0	978	77223031.8
Feb	108.8	89.0	31.4	6.3	78.5	978	76760805.4
Mar	92.5	89.0	31.4	6.3	63.2	978	61816898.8
Apr	74.0	89.0	31.4	6.3	46.3	978	45253522.0
May	37.1	89.0	31.4	6.3	15.3	978	14954965.8
Jun	0.0	89.0	31.4	6.3	0.0	978	0.0
Jul	0.0	89.0	31.4	6.3	0.0	978	0.0
Aug	0.0	89.0	31.4	6.3	0.0	978	0.0
Sep	0.0	89.0	31.4	6.3	0.0	978	0.0
Average Annual Runoff (2024-2030)							331367755

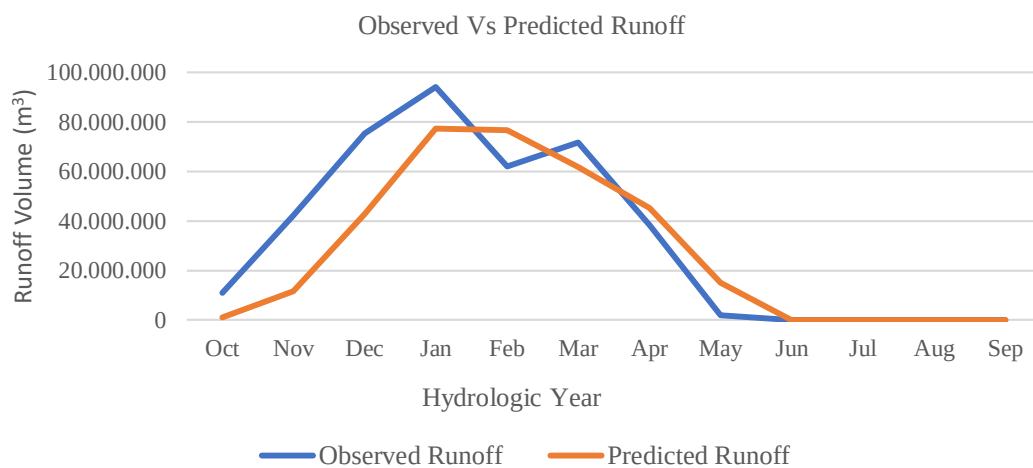


Figure 12. Relationship between the observed and predicted runoff for the whole hydrologic year.

4. Discussion

This study evaluated five deep learning architectures for seasonal precipitation and runoff forecasting in the TaqTaq-Dokan Basin, an area that experiences winter floods and summer water shortages downstream of Dokan Lake. The results show that deep learning models can reliably capture the basin's strong seasonal hydrological cycle, and they provide a practical basis for long-term water management planning.

4.1. Model Performance and Selection of RNN

Among the five architectures tested, the Recurrent Neural Network achieved the lowest error across all metrics: MSE = 1009.65, RMSE = 31.78, and MAE = 23.09 (Table 10). This is consistent with the ability of RNNs to model temporal dependencies in hydrological time series. The ranking of models was: RNN > CNN > LSTM > GRU > MLP. The superior performance of RNN over LSTM and GRU in this case likely reflects the relatively short sequence length and the clear annual seasonality of rainfall in northern Iraq, where a simpler recurrent structure may generalize better than deeper, more parameter-heavy models. In contrast, the MLP recorded the highest errors, which aligns with findings that feed-forward networks are less effective for sequential rainfall

data compared to recurrent or convolutional structures (12)(48)(24).

This result agrees with regional studies. Tahseen and Ali (2025) reported that ANN outperformed MLR, XGBoost, SVR, and RF for monthly rainfall in Erbil, and Muhamad and Ali (2025) found ANN superior to MLR, ANFIS, LASSO, and ELNET in Pirmam. However, other studies show that hybrid or convolutional-recurrent models can be optimal in different contexts: Alqahtani et al. (2023) found a CNN-BDLSTM best for southern Iraqi marshes, while Aizansi, Ogunjobi and Ogou (2024) reported MLP > LSTM in Benin. Thus, no single architecture is universally best; performance remains site- and data-dependent, as also noted by Chen et al. (2022) for Turkey, where LSTM outperformed RF

4.2. Seasonal Patterns and Hydrological Interpretation

All five models reproduced the observed pattern: peak rainfall and runoff in December–February, with zero runoff from June to September (Table 11, Table 12). This reflects the Mediterranean-type climate of the basin, where 614 mm of average annual rainfall is concentrated in 8 months and summer rainfall is below the SCS-CN initial abstraction threshold (0.2S) (Eq. 3). The estimated

average annual runoff for 1987–2021 was 396.56 million m³, while the 2024–2030 forecast averages 331.37 million m³ yr⁻¹ (Table 12). The reduction in the forecast period is driven by lower predicted winter peaks, but the magnitude remains substantial. With a basin-wide CN of 89, steep topography (313.5–1671.99 m), and limited infiltration, intense winter rainfall is converted rapidly to surface runoff, which is consistent with the flood events reported in 1988 and 2019 when Little Zab discharge reached ~1200 m³/s (IMOS, 2025).

4.3. Water Resource Implications

The forecast of >330 million m³ of unused runoff annually indicates a significant unutilized water resource in the TaqTaq-Dokan Basin. At present, this volume is discharged to the Little Zab River during high-rainfall months, contributing to downstream flooding and loss of agricultural and residential land (IMOS). Similar challenges have been reported elsewhere in Iraq, where AI-based forecasting is increasingly seen as a tool to improve water security (Hamaamin, 2025; Latif, Mohammed and Jaafar, 2024). The use of a hydrologic year (Oct–Sep) and CF interpolation for missing 1990–1992 data also improved model stability, following standard practice in hydrology.

4.4. Limitations and Future Work

Three limitations should be noted. First, the models were trained on a single meteorological station, which may not fully represent spatial variability across the 978 km² basin. Second, runoff was estimated using the SCS-CN method, which assumes AMC II and does not explicitly model infiltration dynamics or reservoir operations at Dokan Dam. Third, climate non-stationarity was not incorporated; future changes in temperature or rainfall intensity could alter the seasonal pattern (Al-Ansari and Knutsson, 2011). Future work could integrate multi-station data, physically based hydrological models, and climate projections to improve robustness.

Overall, the findings confirm that deep learning, particularly RNN, is a reliable tool for annual precipitation and runoff prediction in the TaqTaq-Dokan Basin. The models capture seasonal variability with sufficient accuracy to support planning. Given the forecast of ~331 million m³ yr⁻¹ of unused runoff, there is a clear case for strategic water conservation measures, including ponds, dams, and reservoirs in high-precipitation zones, to reduce flood risk and enhance water availability during summer droughts.

5. Conclusion

This research applied five deep learning architectures to predict monthly precipitation and estimate surface runoff in the TaqTaq-Dokan River Basin using data from IMOS Koya Station (1987–2024). Among the models, RNN provided the highest accuracy for monthly precipitation forecasting. All models captured the basin's strong seasonal cycle with winter peaks and summer drought. The hydrological analysis indicates an average annual runoff of 396.56 million m³ for 1987–2021 and a

forecast of 331.37 million m³ yr⁻¹ for 2024–2030. This represents significant seasonal water volume that is currently unregulated and contributes to flood risk in the region.

Author Contributions

The percentages of the authors' contributions are presented below. All authors reviewed and approved the final version of the manuscript.

	M.K.O.	A.O.
C	50	50
D	50	50
S	50	50
DCP	50	50
DAI	50	50
L	50	50
W	50	50
CR	50	50
SR	50	50
PM	50	50
FA	50	50

C= concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The authors declare that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

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