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Research Article

Comparison of Long-Short-Term Memory and Gated Recurrent Unit Based Deep Learning Models in Prediction of Streamflow

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Abstract

The increase in the world population and the resulting demand for water and energy place an increasing pressure on water resources. Machine learning (ML) plays an active role in predicting river flows. The recurrent neural network (RNN) model, which is one of the ML methods, was insufficient due to the lost gradient problem in repetitive data sets. Long short-term memory networks (LSTM) allow network cells to forget some of their previously stored memory. Another method, the gated repetitive unit (GRU), updates the memory and solves the loss problem. GRU is fast as it has less training parameter and uses less memory, whereas in LSTM model it is more accurate on dataset as longer sequences are used. Since the data set obtained from the flow data of the Fatopaşa flow measurement station (FMS) (2000-2009) on the Euphrates River (E21A035) has medium size and repetitive values, these two models were compared with the data obtained from this station in the study. Adadelta, Adagrad, FTRL, SGD, RMSprop, Nadam, Adamax, Adam improvers were tested for the study. Considering the R^2, MAE, RMSE statistical evaluation criteria, it was seen that Adam and Adamax optimizers gave better results and it was decided to use these optimizers that were most suitable for the data. MAE, MSE and LogCosh loss functions were used in the study. When the performance of LSTM and GRU models are analyzed, it is observed that better results are obtained than the GRU model, with values of 0.3346 RMSE, 0.1464 MAE and 0.9718 R^2.

Keywords: Streamflow, Long-short term memory, gated recurrent unit, river management, water resources.

Nehir Akım Tahmininde Uzun-Kısa Süreli Bellek ve Geçitli Tekrarlayan Birim Model Tabanlı Derin Öğrenme Modellerinin Karşılaştırılması

Öz

Dünya nüfusundaki artış ve bunun sonucunda ortaya çıkan su ve enerji talebi, su kaynakları üzerinde artan bir baskı oluşturmaktadır. Makine öğrenmesi (ML), nehir akışlarını tahmin etmede etkin bir rol oynamaktadır. ML yöntemlerinden olan tekrarlayan sinir ağı (RNN) modeli, tekrarlayan veri setlerinde kaybolan gradyan sorunu nedeniyle yetersiz kalmıştır. Uzun kısa süreli bellek ağları (LSTM), ağ hücrelerinin önceden depolanmış belleklerinin bir kısmını unutmasına izin verir. Diğer bir yöntem olan geçitli tekrarlayan birim (GRU) ise hafızayı günceller ve kayıp problemini çözer. GRU'nun eğitim parametresi daha az olduğu ve daha az bellek kullandığı için hızlıdır, LSTM modelinde ise daha uzun diziler kullanıldığından veri kümesinde daha doğrudur. Fırat Nehri üzerindeki (E21A035) Fatopaşa akım ölçüm istasyonunun (FMS) (2000-2009) akış verilerinden elde edilen veri seti orta büyüklükte ve tekrarlayan değerlere sahip olduğundan çalışmada bu iki model bu istasyondan elde edilen veriler ile karşılaştırılmıştır. Çalışma için Adadelta, Adagrad, FTRL, SGD, RMSprop, Nadam, Adamax, Adam iyileştiricileri test edilmiştir. R^2, MAE, RMSE istatistiksel değerlendirme kriterleri göz önüne alındığında Adam ve Adamax optimize edicilerin daha iyi sonuçlar verdiği görülmüş ve verilere en uygun olan bu iyileştiricilerin kullanılmasına karar verilmiştir. Çalışmada MAE, MSE ve LogCosh kayıp fonksiyonları kullanılmıştır. LSTM ve GRU modellerinin performansı analiz edildiğinde, GRU modelinden daha iyi sonuçlar elde edildiği, 0.3346 RMSE, 0.1464 MAE ve 0.9718 R^2 değerleri ile gözlemlenmiştir.

Anahtar Kelimeler: Nehir akımı, Uzun-kısa süreli bellek ağları, geçitli tekrarlayan birim, nehir yönetimi, su kaynakları

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1. Introduction

Water is one of the most important substances for the survival of all living things on earth. Since the amount of water on earth is constant and the need for water increases as the population increases, planning and managing water resources as accurately as possible has recently been one of the most important issues in hydrology (Nazimi, 2021). In Turkey, economically current water potential is 110 km^3 and 57km^3 of the potential water is consumed. Also, 77% of this amount is used in irrigation, 23% in drinking-use and industry. Considering that the irrigation sector targets 65% of this amount, provided that all of our consumable water potential is used in 2030; It is stated that achieving this goal depends on water saving and the provision of sustainable water resources (Yavuz and Yavuz, 2021; Hasırcı, 2021).

One of the important points to ensure sustainability is the estimation of river flows. Recently, there is an increasing need for a higher spatiotemporal resolution in the analysis and modelling of water-energy demand, as they would be more useful for policy analysis and infrastructure planning in both water and energy systems. In summary, short-term or long-term flow estimations have an important place in effective water management. With the development of deep learning models depending on artificial intelligence, there are many hydrological models in the literature (Kılınç, 2021). Recently, important progress has been made in Deep learning (DL), Machine learnnig (ML) and data knowledge. Convulational Neural Network (CNN), Long-short term memory network (LSTM), Gated recurrent unit (GRU), Recurrent neural network (RNN), Restricted Boltzmann Machine (RBM) are some of the popular DL models used in the literature. The DL approach, known as LSTM, overcomes the problems RNNs face and maintains long-term timer knowledge of time series datum (Khan and Yairi, 2018; Zhou et al. 2019). Long Short-Term Memory Networks are a proprietary recursive neural network architecture designed to model temporal sequences and their long-range dependencies more accurately than traditional recurrent neural networks. (Hochreiter and Schmidhuber, 1997; Gers et al. 1999). Another popular DL model GRU has much lower training time than the LSTM model, as its performance is similar to the LSTM (Day and Salem, 2017). The GRU is optimized and condensed on the basis of LSTM, which has two gates named reset gate and update gate to control the flow of information. Benefiting from the structure, the forecasting speed of GRU is effectively improved and maintain the strength of LSTM at the same time (Wang et al. 2020). GRU has emerged as a powerful tool in various applications encompassing time series prediction, such as streamflow prediction, machine health monitoring, wind speed prediction and traffic flow prediction (Zhao et al. 2018). In the literature, streamflow forecasting models have been used for river flow forecasting in many studies (Demir and Tona, 2021; Cebe and Bilhan, 2021; Soyaslan, 2019; Zhao et al. 2021; Apaydin et al. 2020). The proposed study contributes to the algorithm-based prediction model literature. Comparing the success of both models in forecasting will enable the model to be used to produce efficient solutions to be further strengthened and applied in future studies. The results produced in the study were compared by considering other methods in the current literature. The statistical significance of the comparison of the proposed method with the methods in the literature has also been demonstrated. In the Bulam River (Fatopaşa) on the Euphrates basin, daily time series were obtained from the Flow Measurement Station (FMS) numbered E21A035 and their applicability in flow estimation was investigated by the comparative analysis of the GRU and LSTM models.

2. Material and Method

2.1. Study Region and Dataset

The Euphrates Basin defines the border of the provinces of Tunceli, Erzincan, Elazig, Diyarbakir, Malatya, Adıyaman, Gaziantep, Şanlıurfa, starts from the east of Turkey, passes from the north to the south, and then joins with the Tigris basin in Iraq and Basra Province of Iraq. The Euphrates then empties into the Persian Gulf. This basin has an area of 127304 km^2 and an average height of 1009m, making it one of the largest water basins in Turkey. The average annual precipitation in this basin is 540.1 mm/year and the average annual flow is 31.61 km^3. This basin is the largest in Turkey in terms of average annual flow (Nazimi, 2021).

The average annual flow of the Euphrates is around 32 billion cubic meters, and 80% of this amount is located in the upper basin to the north of the Keban Dam. Its maximum flow in April and May corresponds to 42% of the total annual flow. Euphrates River flow values vary in the basin. While the flow is 200 m^3/s in the winter months due to the precipitation in the form of snow, this figure increases up to 2000 m^3/s in the spring with rain and snow melts. The flow, which decreases rapidly in July, decreases to the minimum level in September-October. The fact that the temperature is sufficient especially in the middle parts of the Euphrates River basin and that the drought creates a long period of time during the vegetation period increases the importance of the precipitation falling in the high regions. This situation shows the importance of precipitation in the middle and lower Euphrates Basin. In addition, the examination of the factors created by the river regime on the basin has been effective in the selection of this region as the subject of study (Yıldırım, 2006; Özcan et al. 2013).

The Euphrates river ranks first among the total water potentials of the rivers in Turkey with a share of 24.93%. While scenarios are being written such that fresh water is insufficient and therefore water wars may be experienced, this water potential of the Euphrates river is an important factor for the socio-economic development of the region; The fact that there is a cross-border water also raises the concern that there may be water sharing crises among the partner countries in the future. In this respect, if the river water is used effectively and efficiently and the problems arising in river management are minimized, it has the feature of being a solution to potential water scarcity problems for Turkey and partner countries. In this respect, the geopolitical and socio-economic importance of the river has been influential in the selection of this region in the study (Bilbay, 2014).

Also, the FMS was selected in accordance with the conditions of being on important branches of the Euphrates River Basin shown in Figure 1. In the study, 10-year, daily streamflow data among the years 2000-2009 belonging to the Bulam River Fatopaşa FMS located in the Euphrates Basin, numbered E21A035, were used. The daily streamflow data required for this study has been obtained from the printed and digital sources published by the General Directorate of Electrical Works and Survey Administration (EIEI) and the General Directorate of State Hydraulic Works (DSI).

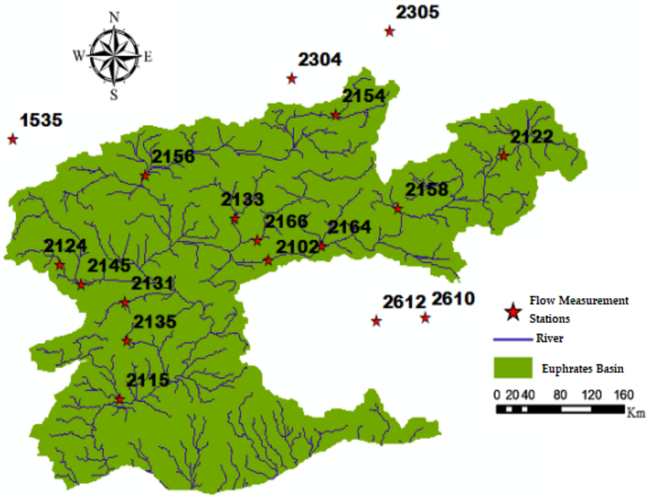

Figure 1. Location of Fatopaşa FMS at Euphrates River Basin

Fatopaşa FMS (E21A035) is located in the Euphrates River Basin at 37°59'38" north latitude and 38°14'13" east longitude. The annual flow data of the station is 3,534 m^3/s. Its total drainage area is 154.8 km^2 and its height is 1252m. As shown in Figure 2, the minimum and maximum flow rates of the river station are 2.3 m^3/s and 49.8 m^3/s, respectively.

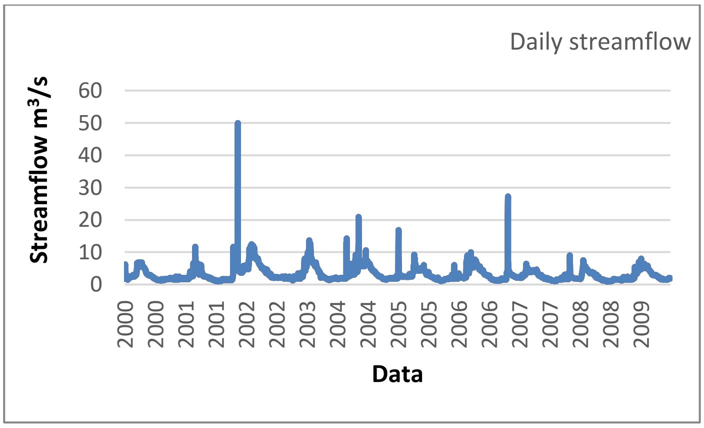

Figure 2. Distribution of daily streamflow for Fatopaşa FMS

In the study, Python 3.9, one of the Python programs, was used to process the input parameters and daily flow data in the models. Daily flow data analyzed using LSTM and GRU models were generated with 50 periods and performance analysis with 8 batch sizes. In the study, performance evaluation was made with many optimizers during the analysis phase and the ADAM optimizer with optimum conditions was used. RMSE was used as the loss function. The data obtained from Fatopaşa station included 10 years of daily flow data between 2000-2009. 80% of the data was obtained as the training set and the remaining 20% as the test set. The obtained data and the models were compared and the performance analysis was carried out with the test data.

In the study, river flows were estimated with the data of Fatopaşa station located on Bulam river. Measurement difficulties may be experienced in flow data due to some meteorological and hydrological factors (difficulty of transportation, measurement problems, etc.). For this reason, when determining the data time intervals, the time intervals when the data were complete were taken into account as much as possible.

2.2. Method

2.2.1. Long-Short Term Memory

LSTM networks are basically an effective method in explaining past information to current information and predicting future information. As shown in Fig. 3, LSTM blocks have three gates. These gates perform the writing, reading and resetting of the cell. All cells are controlled by these three gates (Fang et al. 2020). The entrance gate controls the input information to the open cell, determines how much information is transferred to the new data using the past gate, and controls how much information is used when calculating the output using the exit gate.

$$gt = \sigma(Ugxt + Wght\text{-}1 + bf) \quad (1)$$

$$it = \sigma(Uixt + Wiht\text{-}1 + bi) \quad (2)$$

$$cet = \tanh(Ucxt + Wcht\text{-}1 + bc) \quad (3)$$

$$ct = gt * ct\text{-}1 + it * cet \quad (4)$$

$$ot = \sigma(Uoxt + Woht\text{-}1 + bo) \quad (5)$$

$$ht = ot * \tanh(ct) \quad (6)$$

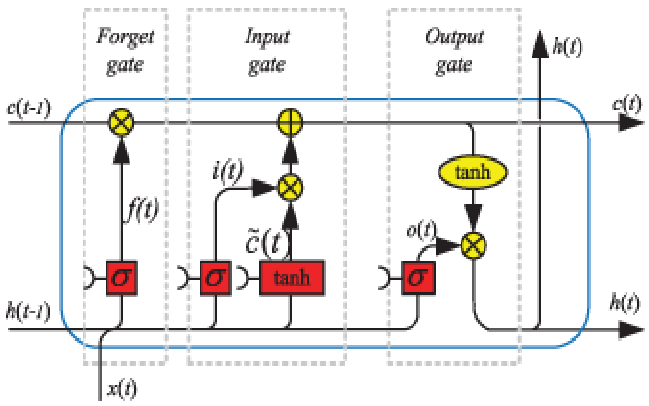

Figure 3. The structure of the LSTM model cell

U and W are known as the input weights of different gates. All these controllers determine the amount of information obtained from the previous cycle and the amount of information transferred to the new state.

2.2.2. Gated Recurrent Unit

GRUs are special variations of RNNs (Fig. 4). The structure of a GRU and the equations of GRU that govern its functions are listed in (7)– (10) (Sing et al. 2017).

$$rt = \sigma(Wr \cdot [ht\text{-}1,xt] + br) \quad (7)$$

$$eht = \tanh(W \cdot [rt \cdot ht\text{-}1,xt]) \quad (8)$$

$$zt = \sigma(Wz[ht\text{-}1,xt] + bz) \quad (9)$$

$$ht = (1 - zt) \cdot ht\text{-}1 + zt \cdot eht \quad (10)$$

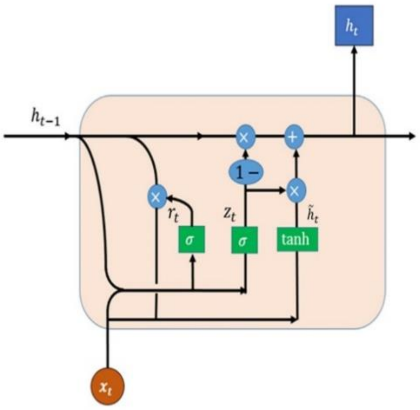

Figure 4. The structure of the GRU model cell

3. Results and Discussion

Predictive models were validated using test data and analysed using the evaluation criteria. With the selected evaluation parameters LSTM and GRU models were applied to forecast daily stream flows at Bulam river Fatopaşa FMS.

Fig. 5 (a)-(f) GRU, Fig. 6 (a)- (f) LSTM indicated the distribution of data. The model with the less deviation was shown in GRU model using Adam optimizer with MAE loss in Fig. 6 (a), while the model with the highest deviation was the model in Fig. 7 (e). It was seen that LSTM model using the MSE loss function and ADAMAX optimizer function in LSTM model, Fig. 7 (f) of Adamax optimizer and LogCosh loss function showed the best result.

Table 1 showed the results of GRU and LSTM models using different loss functions and optimizers according to performance evaluation criteria. As shown in table, RMSE criterion, the best result for GRU was found 0.3346 from the model in which the Adam optimizer and the MAE loss function were used; the worst conclusion was obtained from the model using Adamax optimizer and MSE loss function with a value of 0.4615. From the model where Adamax optimizer and LogCosh loss function were used with 0.3487 value of the best conclusion for LSTM; the worst conclusion is obtained from the model using Adamax optimizer and MSE loss function with a value of 0.4483. According to this criterion, the GRU model was more successful than the LSTM model, and the MSE loss function had the worst result in both models.

According to MAE performance criterion, the best result for GRU was 0. 1464 from the model in which the Adam optimizer and the MAE loss function were used; the worst result is from the model where Adamax optimizer and MSE loss function were used with a value of 0.2169; The best result for LSTM was 0. 1545 with the value of Adam optimizer and the MAE loss function from the model; the worst conclusion was obtained from the model using Adamax optimizer and MSE loss function with a value of 0.2135. After the best values of this criterion were compared, it was observed that the GRU model was more successful and the MSE loss function had the worst performance.

According to STD performance criteria, the best result for GRU with a value of 0.1595 from the model in which the Adam optimizer and the MSE lost function were used; The worst result was from the model using Adamax optimizer and LogCosh loss function with a value of 0.1680; from the model where the best result for LSTM was 0.1647 with the value of Adam optimizer and MAE loss function; It is seen that the worst conclusion was obtained from the model using the Adam optimizer and MSE loss function with a value of 0.2135. According to this criterion, the most successful result belongs to the GRU model, and the Adam optimizer performed better in both models.

Finally, according to the R^2 performance criterion, the best result for GRU with 0.9718 value from the model where Adam optimizer and MAE loss function were used; The worst result was from the model where Adamax optimizer and MSE loss function were used with a value of 0.9494; From the model in which Adamax optimizer and LogCosh loss function were used with a value of 0.9689 for LSTM; the worst conclusion was obtained from the model using Adamax optimizer and MSE loss function with a value of 0.9513. When the best results of this criterion were compared, the GRU model was more successful and the results with the worst performance for both models belong to MSE. Considering all performance criteria; the GRU model was more successful than the LSTM model and the MAE loss function was more successful for both models compared to the other loss functions, and the MSE loss function was less successful than the other loss functions, and when the optimizers were compared, the Adam optimizer was generally more successful. The technological progress and capacity reduction of high-water-consuming technologies could reduce the water stress. Both water demand side and water supply side estimations were suggested to reach the coordinated development of energy with water resources.

Table 1. Forecasting evaluation criteria

	GRU OPTIMIZERS						LSTM OPTIMIZERS					
	ADAMAX			ADAM			ADAMAX			ADAM		
	LOSS FUNCTIONS						LOSS FUNCTIONS					
STATISTICAL METRICS	MAE	MSE	LOG COSH	MAE	MSE	LOG COSH	MAE	MSE	LOG COSH	MAE	MSE	LOG COSH
RMSE	0,4346	0,4615	0,4403	**0,3346**	0,4304	0,4272	0,4380	0,4483	**0,3487**	0,4212	0,4473	0,4331
MAE	0,1773	0,2169	0,1796	**0,1464**	0,2029	0,1846	0,1860	0,2135	0,1555	**0,1545**	0,1703	0,1742
STD	0,1651	0,1628	0,1680	0,1608	**0,1595**	0,1650	0,1654	0,1715	0,1654	**0,1647**	0,1768	0,1662
R^2	0,9556	0,9494	0,9556	**0,9718**	0,9537	0,9551	0,9528	0,9513	**0,9689**	0,9557	0,9515	0,9524

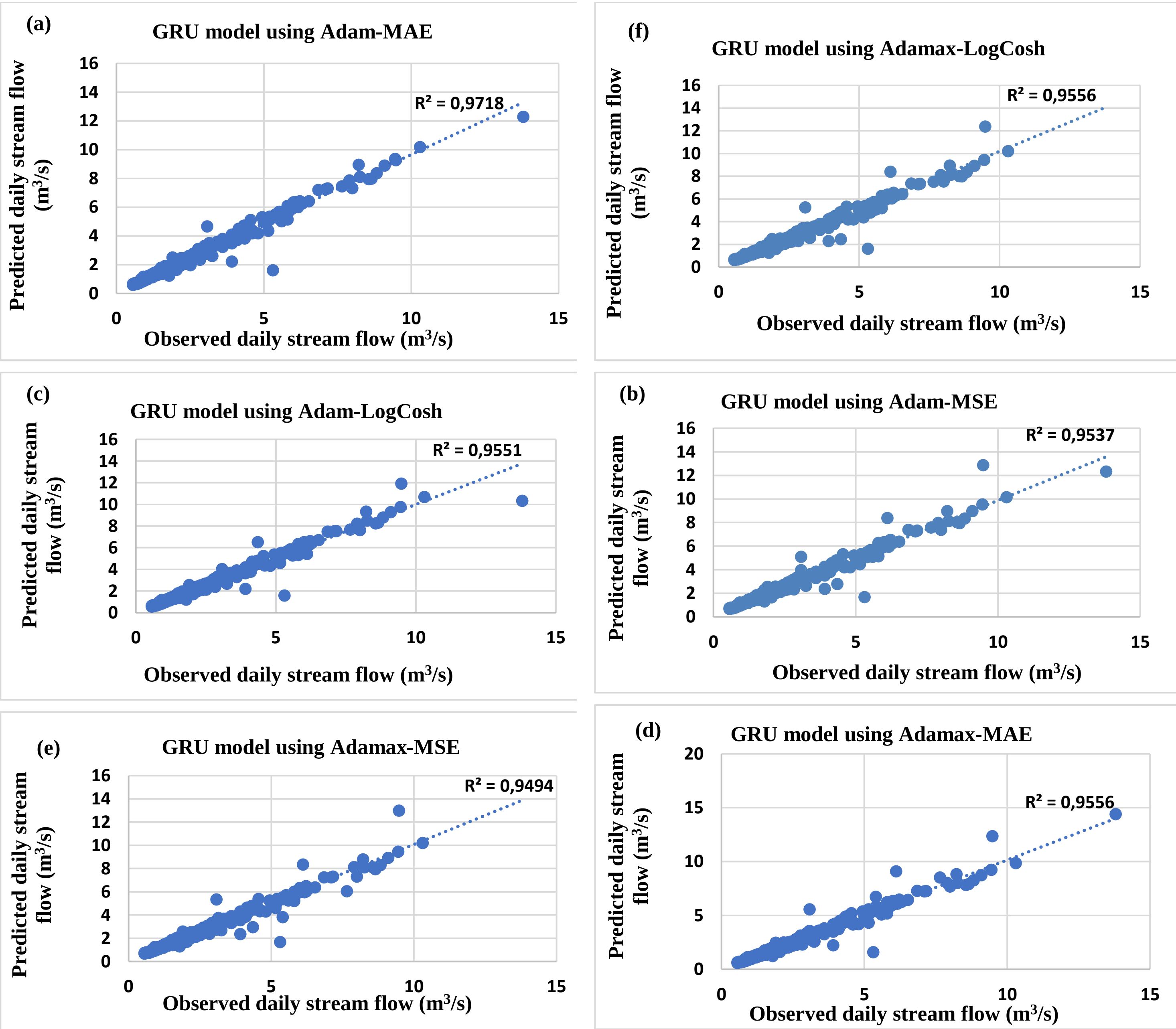

Figure 5. Fatopaşa FMS scatter plots model test results for GRU

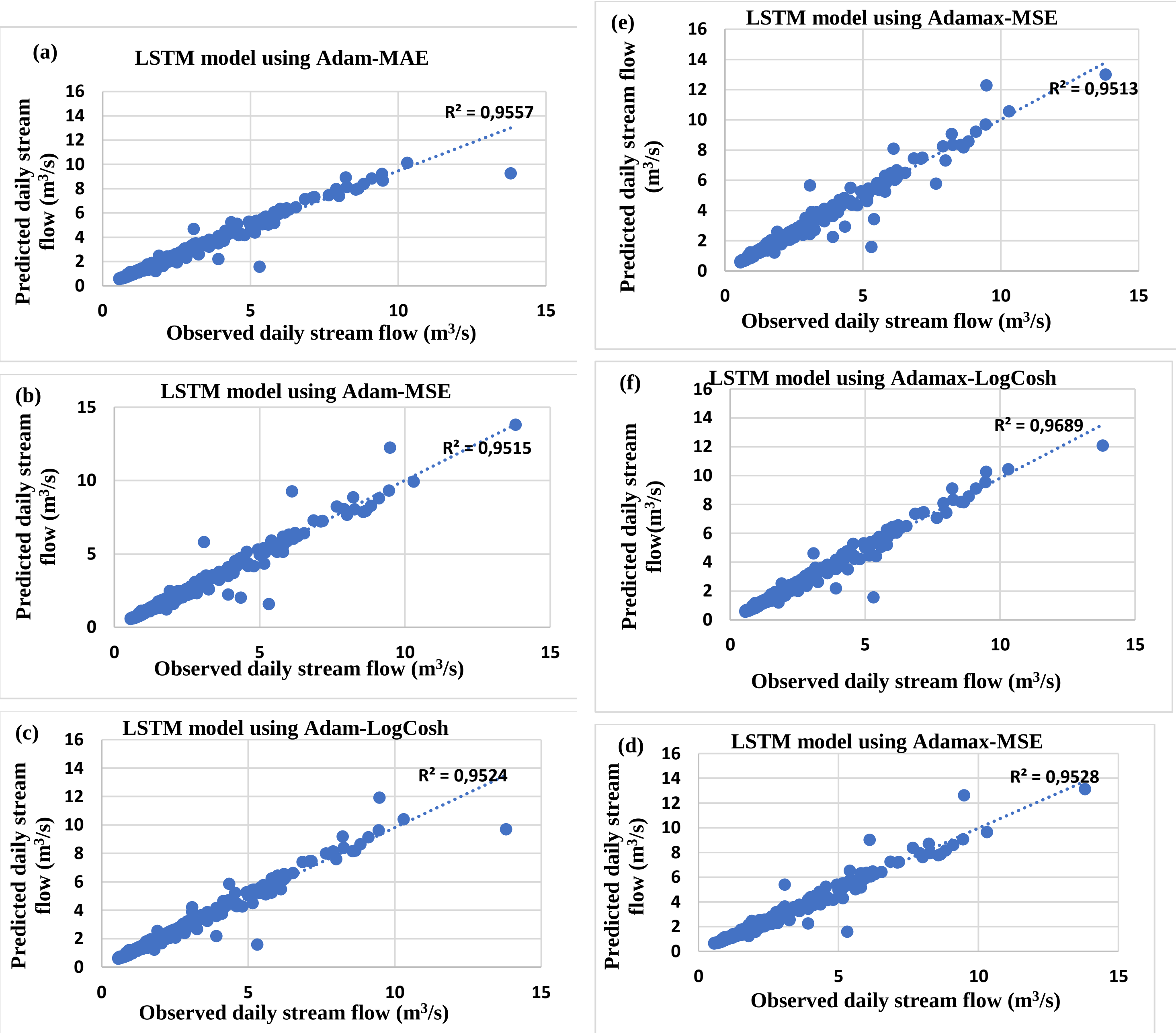

Figure 6. Fatopaşa FMS scatter plots model test results for LSTM

4. Conclusions and Recommendations

It is essential to use reliable flow estimates when planning regulations and applications in flows. Traditional flow estimation methods can be insufficient to make effective estimates with the uncertainties of the system and the nonlinear properties of the system. When the GRU and LSTM models, which are among the artificial intelligence methods that give effective results in the studies they were used in, were examined, they were found to be suitable as a solution method.

This study viewed a method of a DL model based on GRU and LSTM were improved to estimate the streamflow of the Euphrates River. While the LSTM and GRU methods were tested with the training and test data in the study, it was modeled using all optimizers (Adadelta, Adagrad, FTRL, SGD, RMSprop, Nadam, Adamax, Adam) and using loss functions appropriate for regression (MAE, MSE, LogCosh). The optimizers and loss functions below R^2 value of 0.93 were ignored and were not included in the study. The results of the achieve of the GRU and LSTM models were evaluated by comparing the Adam and Adamax optimizers with R^2 value of 0.94 and above according to other statistical evaluation criteria. According to the evaluation method, the GRU model shows better accuracy in the context of ownership of the time series of the streamflow. However, there is still room for improvement in the LSTM streamflow forecasting model. The models can be used as an effective tool for designating proper energy and water resource management strategies in the region.

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