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Improving Monthly Precipitation Forecasting with GRU-LSTM Model in Turkey

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Abstract
Protecting lives and property in Turkey requires reliable precipitation forecasts due to the country's susceptibility to extreme weather events like heavy precipitation, flash floods, and typhoons. On the other hand, Predictions enable officials to implement preventive actions and alert the community. Hence, researching forecasting precipitation in Turkey is essential. This research uses two combined deep learning hybrid models of Convolutional Neural Network, Long Short-Term Memory (CNN-LSTM), and Gated Recurrent Units-Long Short-Term Memory (GRU-LSTM) to predict the monthly precipitation of Istanbul and Konya between 2000 to 2023. From the research results, it can be concluded that the GRU-LSTM model is generally better than the CNN-LSTM model in monthly forecasting.

Keywords
GRU, Hybrid Model, LSTM, Precipitation, Prediction

Introduction

The process of precipitation is vital in maintaining the balance of water and energy on a global scale, ensuring the availability of freshwater necessary for survival. However, precipitation plays a crucial role in determining the likelihood of water and weather-related calamities, including droughts and floods (Nielsen et al., 2015). On the other hand, understanding precipitation is essential for analyzing how landscapes evolve, evaluating potential hazards, and determining the effects of climate change.

Precise precipitation forecasts are essential for Turkish farmers to strategize their farming operations efficiently. The success of businesses in tourism, transportation, and energy hinges on accurate rainfall forecasts for decision-making. Accurate forecasts of precipitation are crucial for the success of Turkey's agriculture, water resources management, disaster prevention strategies, infrastructure development plans, and economic pursuits (Aziz and Yucel, 2021).

Part of disaster preparedness involves developing prediction models (Surta et al., 2023). Overcoming challenges associated with heavy rain is possible with deep learning models predicting precipitation. Deep learning models can surpass the limitations of traditional physics-based forecasting by deriving insights from historical data and patterns, resulting in forecasts with greater accuracy and finer spatial detail, as well as the capability to gauge uncertainty in predictions (Espeholt et al., 2022).

Hybrid deep learning models are essential for improving precipitation forecasting by integrating various modeling techniques. Integrating hybrid models into precipitation forecasting systems can improve their generalization capability (Ali et al., 2025). By merging the best qualities of diverse modeling approaches, hybrid models bring forth a hopeful resolution to the hurdles of precipitation forecasting, bolstering the dependability and precision of weather forecasts.

This research uses two deep learning hybrids Gated Recurrent Unit -Long-Shorted Term Memory (GRU-LSTM), and Convolution Neural Network-Long-Shorted Term Memory (CNN-LSTM). Research in this field includes the use of GRU and LSTM methods to forecast daily rainfall for the next month using weather element data for ten (10) years in Palembang, using the Deep learning method (Surta et al., 2022). The results showed that the LSTM model is generally better than the GRU model in daily rainfall forecasting. Also, the GRU-LSTM combined model was used to forecast 15-day rainfall, and the results showed that this model has an acceptable performance with the least error (Sari et al., 2022). In general, deep learning hybrid models have made great progress in the field of meteorology and hydrology (Li et al., 2022; Deng et al., 2022; Dehghani et al., 2023).

This research aims to create two combined CNN-LSTM and GRU-LSTM hybrid models to forecast monthly precipitation for the cities of Istanbul and Konya in Turkey. In this study, an attempt has been made to compare two models by using historical precipitation data from 2000 to 2023 without considering other meteorological parameters and by using data delay.

Materials and Methods

In this research, the precipitation data of two important cities, Istanbul, with coordinates 41.0082° N, 28.9784° E, and Konya, with coordinates 37.8746° N, 32.4932° E, have been used for modeling. Figure 1 shows the location of two selected cities.

Istanbul's climate features a temperate maritime pattern influenced by the Black Sea and Sea of Marmara, with cool, rainy winters (4–6°C averages, occasional snow) and warm summers (23–27°C) moderated by coastal breezes, receiving 800–1,200 mm annual rainfall concentrated in winter (Yazar and York, 2023). Konya's climate is semi-arid continental, characterized by hot summers (daytime highs of 30–35°C) and cold winters (daytime highs of 5°C, nighttime lows of -3°C), with moderate annual rainfall (320–388 mm) concentrated in spring and autumn, and minimal summer precipitation (<10 mm).

Fig. 1. Study region, Istanbul and Konya cities in Turkey

The required data was taken from the Mathematica software database (Wolfram Research, 2008) from 2000 to 2023. Next, the modeling process included implementing three delays for precipitation data and dividing it into training (2018-2000) and testing (2019-2023) sets using an 80% to 20% split, utilizing two CNN-LSTM and GRU-LSTM models. The statistical characteristics of Istanbul and Konya cities, shown in Table 1 and Figure 2, show the monthly precipitation time series.

Tab. 1. Statistical characteristics of precipitation data

Cities	Statistical characteristics	Precipitation (cm)
Istanbul	Max	19.55
	Average	4.46
	Min	0
	STDV	3.53
Konya	Max	14.22
	Average	2.59
	Min	0
	STDV	2.45

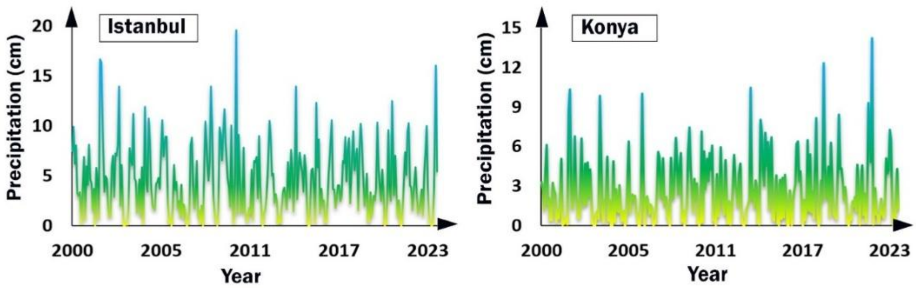

Fig. 2. Monthly precipitation time series for two selected cities

Gated Recurrent Unit

The Gated Recurrent Unit (GRU) is a gating mechanism in Recurrent Neural Networks (RNNs). The GRU and LSTM operate similarly, though the GRU cell stands out by incorporating both the forget gate and input gate into its update gate through a hidden state (Sari et al., 2022). Utilizing the GRU gating mechanism allows users to either update or discard specific features, allowing for precise and efficient processing of sequential data.

The GRU model plays a crucial role in precipitation forecasting as it is a specialized neural network architecture that is well-suited for capturing temporal dependencies in sequential data, such as weather patterns. By effectively modeling the interactions between different variables over time, the GRU model can provide more accurate and reliable predictions of future precipitation levels (Manokij et al., 2019). This is essential for helping meteorologists and other weather forecasters anticipate and prepare for potentially severe weather events, which can significantly impact communities and infrastructure. Furthermore, the GRU model offers advantages over traditional statistical forecasting methods by adapting and learning from new data in real time, making it more responsive to changing weather conditions. This adaptability is particularly important in the context of climate change, where the frequency and intensity of extreme weather events are on the rise (Wang et al., 2024). By incorporating the GRU model into precipitation forecasting systems, forecasters can better understand and predict complex weather patterns, contributing to improved early warning systems and disaster preparedness efforts. Ultimately, the importance of the GRU model for precipitation forecasting lies in its ability to enhance the accuracy and reliability of weather predictions, thereby helping to protect lives and minimize the impacts of severe weather events.

Long-Short Term Memory

The Long Short-Term Memory model, an innovative type of RNN, aims to overcome the vanishing gradient issue found in traditional RNN architectures. By incorporating a memory cell that retains information over extended periods, they are able to grasp long-term dependencies within sequential data (Hua et al., 2019). The trio of gates regulating this memory cell includes an input gate, a forget gate, and an output gate. The structure of the combined GRU-LSTM model is shown in Figure 3.

LSTM models have become a crucial tool for analyzing time series data due to their ability to learn long-term dependencies and patterns within the data. Traditional machine learning models struggle with time series data because they are unable to capture relationships that exist over time effectively. LSTM models, on the other hand, are specifically designed to remember information for long periods of time, making them well-suited for time series analysis. This allows LSTM models to effectively predict future values in a time series based on past data, making them valuable in a wide range of applications such as financial forecasting and weather prediction analysis. In addition, LSTM models are equipped with a forget gate mechanism that helps prevent the model from either overfitting or underfitting the data (Pathan et al., 2021). This mechanism allows the model to selectively remember or forget certain information based on its relevance to the time series analysis. This helps improve the model's generalization capabilities and makes more accurate predictions. Overall, LSTM models are vital for time series analysis as they provide a powerful tool for capturing complex patterns and relationships within temporal data, leading to more accurate and reliable predictions.

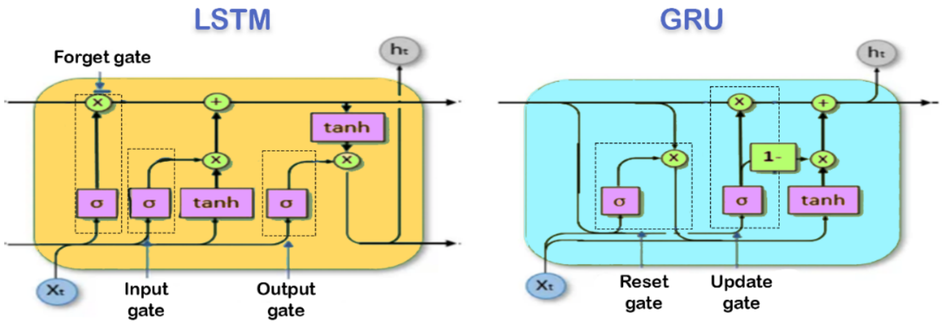

Fig. 3. presents the structure of a common GRU-LSTM model.

Result and Discussion

Evaluation criteria are essential in precipitation forecasting to systematically assess accuracy, reliability, and applicability, ensuring forecasts meet practical needs like flood prediction, agriculture, and disaster management (Liu et al., 2021). These criteria identify model strengths and weaknesses by quantifying errors (for instance, RMSE, Bias) and detection capabilities (for instance, POD, Threat Score), driving improvements in numerical weather prediction and satellite-based systems. Ultimately, evaluation fosters scientific objectivity, refines forecasting models, and supports decision-making across sectors, enhancing preparedness for weather-related risks. The comparison between the prediction results of the models and the test data is done through criteria such as root mean square values (RMSE) and Coefficient of Correlation (r) values.

Table 2 shows the calculated values of the performance measures, such as the correlation coefficient (R) and the root mean square error (RMSE) during the test phase. According to Table 2, it is clear that the GRU-LSTM-M3 model with the lowest error rate (RMSE=3.34) and the highest correlation coefficient (R=0.88) for Istanbul City and the GRU-LSTM-M2 model with an error of (RMSE=2.56) and (R=0.924) for Konya City outperforms the CNN-LSTM model for all scenarios.

Tab. 2. Performance criteria of the two hybrid models in testing periods

Cities	Testing		
	Model	R	RMSE (cm)
Istanbul	CNN-LSTM-M1	0.849	4.981
	CNN-LSTM-M2	0.858	4.336
	CNN-LSTM-M3	0.857	4.460
	GRU-LSTM-M1	0.860	4.197
	GRU-LSTM-M2	0.864	4.030
	GRU-LSTM-M3	0.886	3.340
Konya	CNN-LSTM-M1	0.881	3.672
	CNN-LSTM-M2	0.885	3.634
	CNN-lSTM-M3	0.886	3.598
	GRU-LSTM-M1	0.896	2.980
	GRU-LSTM-M2	0.924	2.568
	GRU-LSTM-M3	0.889	3.486

Figure 4 shows the comparison plot of two combined CNN-LSTM and GRU-LSTM models for the test stage. According to the CNN-LSTM-M2 graph, predictions with high errors are observed at most of the maximum and minimum points. On the contrary, the GRU-LSTM-M3 model has a time series almost similar to the actual values and has errors only at some points.

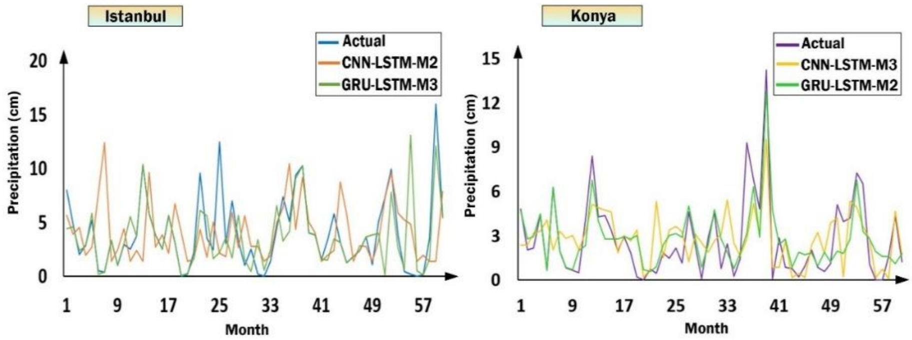

Fig. 4. Comparison plot of two models for the best scenario

Figure 5 also shows the scatter plot for the best scenarios of the CNN-LSTM and GRU-LSTM models. According to this figure, the GRU-LSTM model is highly accurate, with less dispersion than the other models. At Istanbul station, the CNN-LSTM-M2 model with higher dispersion showed low accuracy in precipitation forecasts. On the other hand, the GRU-LSTM-M3 model with lower dispersion has high performance. Also, at Konya station, the CNN-LSTM-M3 model has a high dispersion compared to the GRU-LSTM-M2 model and is less reliable.

The results obtained in this study are consistent with previous research (Surta et al., 2023), and it can be concluded that the GRU-LSTM model is useful for predicting meteorological parameters such as temperature, precipitation, wind speed, etc. (Sari et al., 2022; Chhetri et al., 2020). Ghose et al. (2022) introduced a hybrid artificial intelligence model, CNN-LSTM, combining convolutional neural networks and long short-term memory to enhance prediction accuracy. Using hydrologic data from the Barak River Basin in Assam, India, the CNN-LSTM model demonstrated superior performance ($R^2 = 0.9875$, RMSE = 1.364, IA = 0.9897) compared to standalone CNN models during training. Luo et al. (2024) introduced the LSTM-SelfAttention model. By combining the LSTM neural network for capturing long-term dependencies in time series data with the self-attention mechanism for identifying critical features, the model leverages the strengths of both approaches. A comparison test showed that the LSTM-SelfAttention model outperformed with an improvement of 28% in accuracy over the LSTM and BP neural network models. Yan et al. (2023) researched a data-driven SA-GRU model for hourly urban rainfall-inundation depth prediction, combining a gated recurrent unit (GRU) neural network with simulated annealing (SA) for hyperparameter optimization. Benchmarking against backpropagation, LSTM, and BiLSTM models revealed that SA-GRU achieves high accuracy, with Nash–Sutcliffe efficiency ranging from 0.999 to 0.596 for 1-hour to 8-hour predictions. It also demonstrates significant advantages, such as 20% lower root mean square error, 23.7% faster training speed than LSTM, and 44.2% faster than BiLSTM. Vatanchi et al. (2023) evaluated four models—Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Artificial Neural Networks (ANN), Bidirectional Long-Short Term Memory (BiLSTM), and a hybrid Convolutional Neural Network (CNN)-Gated Recurrent Unit (GRU)-LSTM—for predicting daily streamflow of the Colorado River, using data from 1921 to 2021. Performance metrics (MAE, NRMSE, correlation coefficient, ENS) showed the ANFIS model to be the most accurate, achieving NRMSE = 0.118, MAE = 26.16 (m^3/s), r = 0.966, and ENS = 0.933.

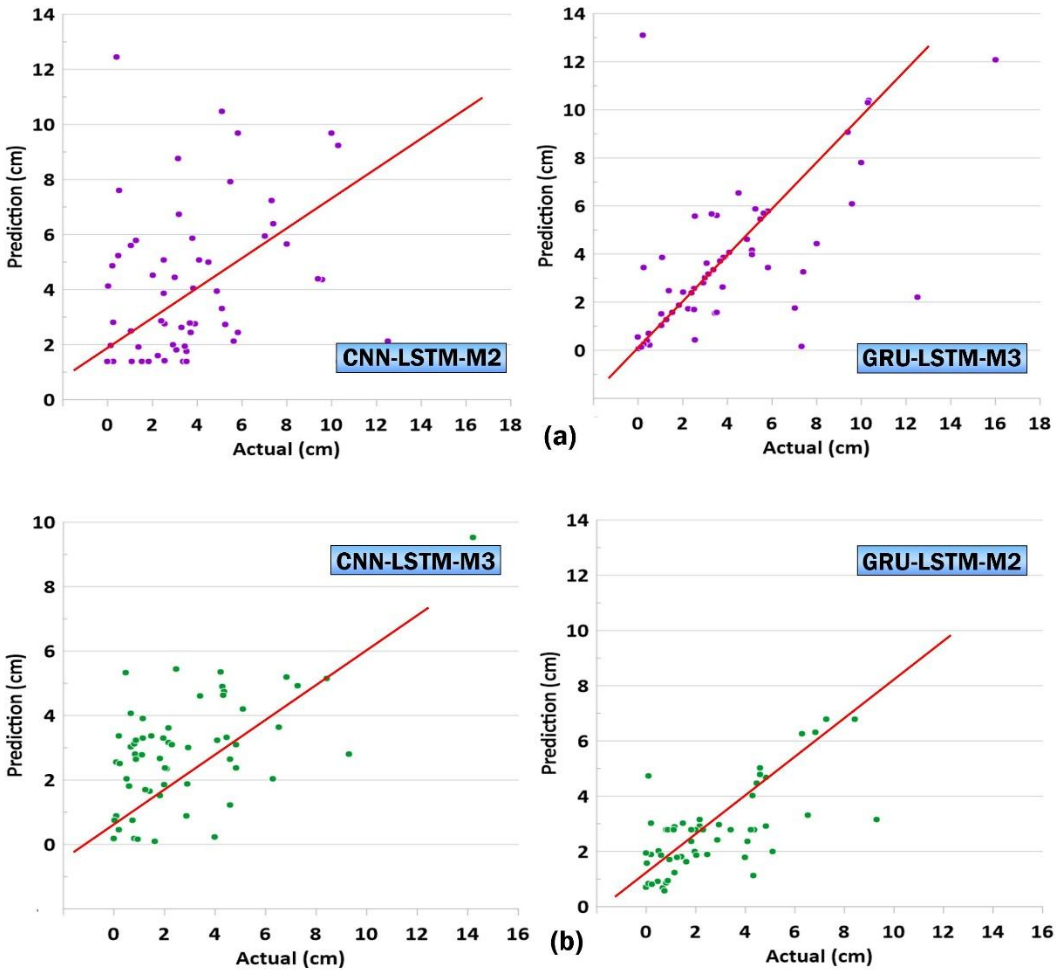

Fig. 5. Scatter plot of two models for the best scenario (a) Istanbul (b) Konya

Conclusion

This research attempted to compare two hybrid deep learning models by delaying precipitation data and selecting it as input. The comparison of forecasted and authentic values suggests that the GRU-LSTM model is superior to the CNN-LSTM model when predicting monthly precipitation in two cities, Istanbul and Konya.

Hybrid models for predicting precipitation, which combine physics-based simulations with machine learning, face several limitations. These include difficulties in extrapolating to extreme events, lack of explainability and physical consistency, and uncertainties in parameterization, especially across diverse spatial scales. They are also computationally expensive and operationally challenging, with limited adoption due to verification complexities. Hybrid models are highly dependent on data quality, inherit biases from dynamical models and machine learning components, and often struggle in data-sparse regions. Additionally, they face challenges in climate change scenarios, such as divergent rainfall projections from global climate models (GCMs) and difficulty capturing nonlinear feedback. Addressing these limitations requires advancements in physics-informed machine learning and seamless integration techniques.

Future research can focus on other hybrid models or the use of meteorological parameters such as temperature, humidity, etc. Also, developing seamless prediction frameworks that merge short- and long-term forecasts is also a priority, alongside refining ensemble techniques to improve accuracy across diverse spatial scales2. Efforts are being made to incorporate novel data sources, such as human influences and land-use changes, while advancing bias correction methods for extreme weather events5. Additionally, enhancing model robustness against overfitting and improving computational efficiency are critical for operational adoption. Future studies may also explore regional climate models and compound climatic event structures to provide more precise local projections.

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