Performance Assessment of Water Level Forecasting Models in the Lake Chad Basin: A Comparison of LSTM, GRU, Transformer, and Informer Models

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Abstract—**This paper compares and evaluates the performance of various deep learning models for forecasting water levels in the Lake Chad basin for the period 2026–2050. The models studied are based on two distinct neural network architectures. The first is based on recurrent networks, namely LSTM and GRU. The first is based on recurrent neural networks, specifically LSTM and GRU. The second relies on attention mechanisms, specifically Transformer and Informer. The experimental results show that models based on the Transformer architecture and in particular its improved version, Informer—outperform other models according to the statistical metrics used. The performance metrics obtained with the Informer model are as follows : MAE** $= 0{,}149$, **RMSE** $= 0{,}202$, **MAPE** $= 0{,}053$, $R^2 = 0{,}862$, **and NSE** $= 0{,}862$. **This model has demonstrated strong predictive power, particularly in capturing long-term dependencies in time series.**

Index Terms— **Water level, Lake Chad basin, Deep learning, Forecasting**

I. Introduction

Lakes play a vital role in ecosystems and water resource management. Understanding future trends is crucial for ecosystem conservation, water resource planning, and reducing the risk of natural disasters, particularly floods. Lakes play a crucial role in storing water for consumption, hydroelectric power generation, and various environmental, agricultural, and industrial uses [1,2]. In recent years, climate change has affected the inflows to Lake Chad, one of Africa's oldest bodies of water [3]. This lake was once the largest of the Saharan paleolakes [4], with an estimated surface area of approximately 361,000 km^2 [5]. Lake Chad is a vital source of freshwater shared by five riparian countries: Cameroon, Niger, Nigeria, Chad, and the Central African Republic [6]. The territorial distribution within this basin is as follows: 43.9% for Chad, 29% for Niger, 7.6% for Nigeria, and 2.1% for Cameroon, with the remaining 17.4% shared among the other countries [7]. The lake supports many regional economic activities, such as agriculture, fishing, livestock farming, mining, and handicrafts. Water level is a fundamental parameter for the management of lake systems; its fluctuations reflect changes in the basin's water volume and influence the system's carrying capacity as well as the self-regulating mechanisms of the hydrological system [8]. Furthermore, changes in lake levels serve as key indicators of the hydrological balance and climate change [9]. A steady decline in water levels could lead to significant water shortages in riparian countries and cause conflicts over water use among various stakeholders, particularly between farmers and herders. Over the past few decades, lake water levels have fluctuated to an unprecedented degree as a result of global warming [9]. In this context, accurate forecasting of water levels—for both lakes and rivers—is essential for water resource planning and reducing the risk of natural disasters, particularly floods [10,11]. Some studies have also highlighted the importance of incorporating physical laws and the intrinsic characteristics of hydrological systems into forecasting models [12]. In response to these challenges, deep learning models have seen rapid development. They have been widely applied in various fields, helping to improve forecast accuracy, flood prevention, and the optimization of water resource management [2]. Recent advances in large-scale time-series models have demonstrated their potential to overcome certain limitations of traditional approaches. These models have achieved remarkable performance in hydrological forecasting and the analysis of temporal dynamics [13,14]. With this in mind, this study aims to predict future trends in water levels in the Lake Chad basin through 2050. The models selected for this study are LSTM, GRU, Transformer, and Informer. These four models were compared and evaluated in terms of their performance in forecasting water levels in the Lake Chad basin for the period 2026–2050, using statistical metrics commonly employed in the literature. The outcomes show that the Informer model is better than the other three models in terms of forecast precision, making it the most suitable model for long-term water level forecasts in the Lake Chad basin.

II. Related Work

This section provides a review of the literature on the use of various deep learning models for forecasting lake water levels based on time series data. Zakaria et al. [10] developed three machine learning algorithms—namely, the multilayer perceptron neural network (MLP-NN), the long short-term memory neural network (LSTM), and Extreme Gradient Boosting (XGBoost)—to forecast water levels in the Muda River in Malaysia. Daily data on water levels and weather conditions covering the period 2016–2018 were used. Des données quotidiennes sur le niveau d'eau et les conditions météorologiques couvrant la période 2016–2018 ont été utilisées. The authors tested various input scenarios to evaluate the models' performance. Rangaraj et al. [13] examined twelve task-specific models and five time-series foundation models, including Chronos, grouped into six categories for a real-world application. The authors evaluated the effectiveness of large-scale time-series models for forecasting water levels in the Everglades in the United States. The results show that the basic Chronos model performs best among all the models compared. Gholami et al. [15] developed a deep learning model based on a feedforward artificial neural network (FFNN) to generate reliable forecasts of long-term water level changes in eight lakes on the Tibetan Plateau (TP) in China. Forecast climate changes (2024–2100) were derived from a set of CMIP6 models based on the SSP2-4.5 and SSP5-8.5 scenarios. Explainable AI, specifically the Shapley Additive Explanations (SHAP) method, was used to analyze the determining factors. Du *et al.* [16] proposed a deep learning approach based on LSTM and GRU networks for forecasting water levels in Lake Vesijärvi, in Lahti, Finland, over 1-, 3-, and 7-day horizons. In this study, the experimental results from both models showed improved performance. Statistical metrics, such as a Nash–Sutcliffe Efficiency(NSE) of over 0.95 and a mean squared error of less than 0.025, demonstrate the effectiveness of recurrent architectures for short-term hydrological forecasting. Wang *et al.* [17] used the theory of hydrothermal coupling equilibrium to quantify the impact of various factors related to climate change. This study incorporates CMIP6 global climate models and uses the Digital Watershed Model to simulate future runoff. A multiple regression model was used to predict future trends in the water level of Lake Qinghai. This model also made it possible to estimate the future extent of flooded areas. Chen *et al.* [18] used a linear model to monitor lake water levels in the arid and semi-arid regions of western China. In this study, lake water levels are considered a direct indicator of regional climate variability. In this study, lake water levels are observed as a direct indicator of regional climate change. These regions are more vulnerable to climate change. A combination of satellite altimetry data from ICESat-1 and CryoSat-2 covering the long period from 2003 to 2021 was used. Chen *et al.* [19] have developed a deep learning framework, Dual-Transformer, for seasonal forecasting of water levels in the Great Lakes of North America, one of the world's largest freshwater systems. This model combines two modified Transformers: Prophet, which predicts underlying trends, and Critic, which refines those predictions. The results indicate that the model can forecast lake levels accurately up to six months in advance. Al-Nuaami *et al.* [20] used an artificial neural network (ANN), a deep learning (DL) neural network model, and an Autoregressive Integrated Moving Average (ARIMA) model to forecast monthly water levels in Lake St. Clair and Lake Ontario over the period 1981–2021. Statistical metrics such as root mean square error (RMSE), the coefficient of determination (R^2), and mean absolute percentage error (MAPE) were used to compare the models' performance.

Idriss *et al.* [21] proposed a deep learning model based on the Transformer architecture to generate accurate water level forecasts for the Lake Chad basin. The results of the proposed model were compared to those of LSTM and GRU models. Idriss *et al.* [22] have presented a review of the literature on lake water level forecasting. This study provides a comprehensive survey of the various machine learning methods used in this field, while also highlighting the latest models and approaches.

III. Methodology

This study compares and evaluates deep learning models based on LSTM, GRU, Transformer, and

Informer architectures. These models have facilitated the forecast of future water level trends in the Lake Chad basin through 2050.

A. Study Scope

The Lake Chad basin covers an area of approximately 2 434 000 km^2, extending between 6° and 24° north latitude and between 8° and 24° east longitude. This basin encompasses five riparian states: Chad, Cameroon, Niger, Nigeria, and the Central African Republic. Ranked 8^e among the world's geological basins and 4^e in Africa, it is a vital resource for local communities. Lake Chad serves as a vital economic lifeline, despite recent security challenges linked to Boko Haram. It remains an area with significant agricultural, pastoral, and fishing activity. In addition, it currently provides services to more than 49 million people. The figure. 1 shows a map of the Lake Chad basin.

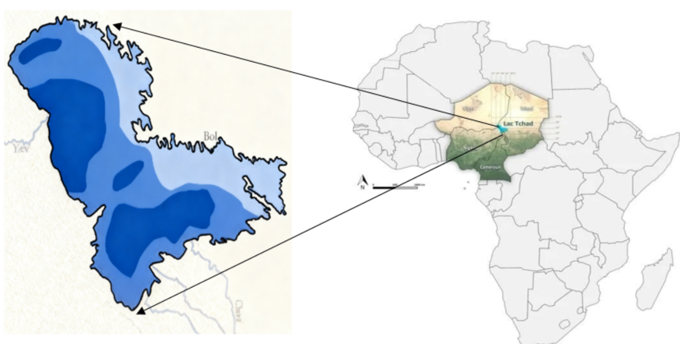


Fig. 1. Location map of Lake Basin, Chad.

B. Data Description

The data used in this study cover the period from 1960 to 2025 and pertain to water levels in the Lake Chad basin. They were recorded at the Bol weather station, located in the Lake Chad region of Chad, by the National Meteorological Agency of Chad (ANAM-Chad). Monthly water level observations were used as input data for the models. The figure. 2 shows the trend in monthly water levels in the Lake Chad basin from 1960 to 2025.

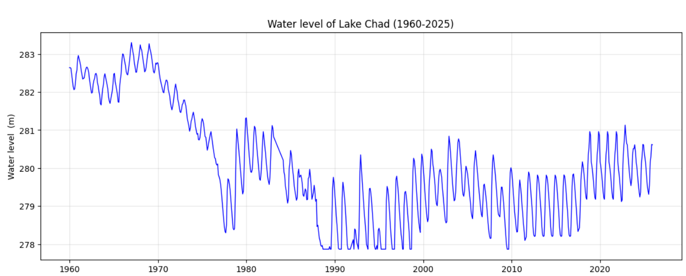
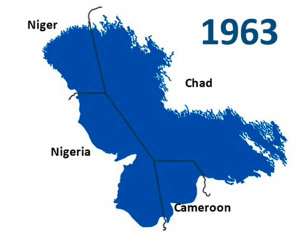
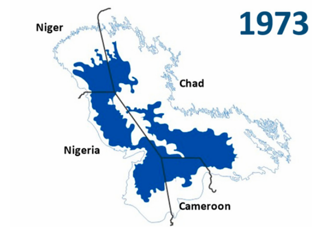


Fig. 2. Changes in monthly water levels in the Lake Chad basin (1960–2025).

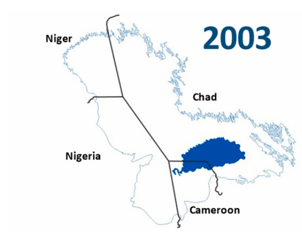
Today, the use of satellite imaging technology makes it possible to effectively monitor water level trends in Lake Chad. The figure. 3 illustrates the NASA report highlighting changes in the surface area of Lake Chad between 1963 and 2021. It shows that Lake Chad has lost a significant portion of its surface area.



(a) oct.31, 1963, Argo Satellite Photograph - Lake Chad



(b) January 1973, Landsat1(path/row 198-199/50-51) - lake Chad



(c) May 2003, Landsat7(path/row 184-186/50-51) - lake Chad

(d) May 2021, Landsat8(path/row 184-186/50-52) - lake Chad

Fig. 3. Trends in the shrinking volume of Lake Chad, adapted from USGS Earthshots. "https://eros. usgs.gov/media-gallery/earthshot/lake-chad-west-africa (accessed on 8 March 2023)" [7].

The figure. 4 provides an overview of the methodology used in this study.

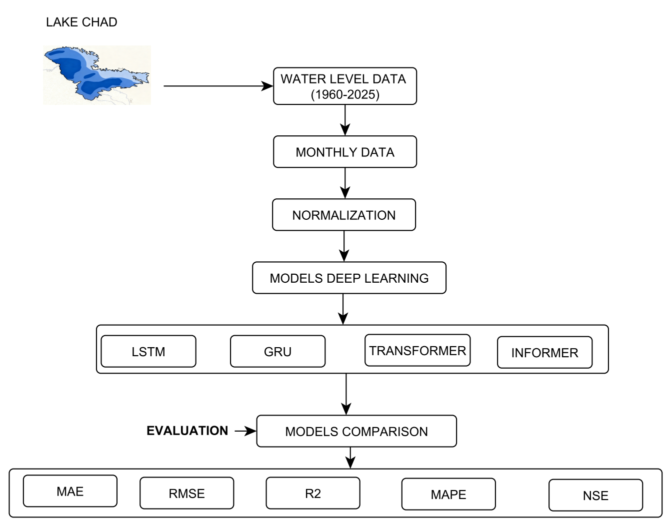


Fig. 4. Flowchart of the proposed methodology for forecasting water levels in Lake Chad.

C. Deep learning models

The four deep learning models selected—namely LSTM, GRU, Transformer, and Informer—were chosen for their ability to capture complex temporal dependencies in hydrological time series.

*1) **LSTM-based Models**:* The LSTM network is a type of recurrent neural network (RNN) that has been widely used by the scientific community in recent years. This model is capable of capturing long and complex temporal dependencies. Furthermore, the LSTM model was first introduced by Hochreiter and Schmidhuber [23]. The LSTM model has been applied in various fields, such as river flood forecasting and anomaly detection [24], as well as short-term railway transport forecasting [25].

*2) **GRU-based Models**:* Gated Recurrent Units (GRUs) are a promising alternative to LSTM networks for time series forecasting. Thanks to their simplified internal structure, GRUs reduce the computational complexity associated with LSTMs while maintaining good performance. This model has been successfully used in multivariate time series forecasting [26].

*3) **Transformer-based Models**:* The Transformer model has emerged as a promising alternative to traditional sequential architectures, such as LSTM and GRU, for time series processing. It is attracting growing interest within the scientific community, particularly for the forecasting of multivariate time series [27], as well as in other application areas [28].

*4) **Informer-based Models**:* Informer is a powerful model based on the Transformer architecture, particularly suited for forecasting long time series. It enhances the attention mechanism to effectively process relevant information in long time series [9]. This model has been successfully applied in several fields requiring the modeling of long-term dependencies [29].

*5) **Model Performance Assessment** :* Various statistical metrics were used to evaluate and compare the performance of deep learning models for forecasting water levels in the Lake Chad basin, namely MAE, RMSE, MAPE, R^2, and NSE.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\|y_i - \hat{y}_i\| \tag{1}$$

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

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{3}$$

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left\|\frac{y_i - \hat{y}_i}{y_i}\right\| \tag{4}$$

$$\text{NSE} = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{5}$$

IV. Results

Models predicting future water level trends in the Lake Chad basin through 2050 were tested using historical data covering the period from 1960 to 2025. This data was provided by ANAM (Chad's National Meteorological Agency). A monitoring station located in Bol, in the Lake Chad region, has been recording the lake's water level on a monthly basis for several years. Several statistical metrics were used to evaluate the performance of deep learning models, including LSTM, GRU, Transformer, and Informer. The metrics used are MAE, RMSE, MAPE, R^2, and NSE. The figure. 5 shows historical water level trends (1960–2025) as well as the projections from the four models for the period 2026–2050. A dotted vertical line marks the transition between the past and the future. During the historical period, the results show significant seasonal and interannual variability in water levels, accompanied by an overall downward trend between the 1960s and 1990s, followed by a period of relative stabilization. This trend is consistent with hydrological observations of Lake Chad. For the forecast period, all models indicate a general downward trend in water levels, followed by a gradual stabilization toward the end of the forecast period.

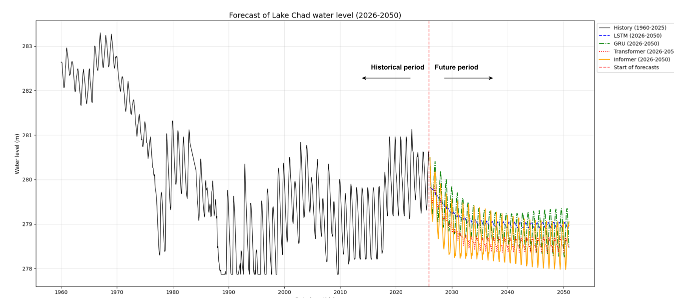


Fig. 5. Monthly water level forecast for the Lake Chad basin for the historical period (1960–2025) and the future period (2026–2050).

To evaluate and compare the performance of these deep learning models, several statistical metrics were used to identify the best-performing model. Two scenarios were tested using different parameter configurations. For Scenario 1, the LSTM and GRU were configured with the following parameters : `input_dim = 1`, `hidden_dim = 128`, `num_layers = 2` et `output_dim = 12`. The Transformer has been configured with the following settings : `input_dim = 1`, `d_model = 128`, `n_head = 8`, `num_layers = 3` et `output_dim = 12`. The Informer has been configured with the following settings : `input_dim = 1`, `d_model = 64`, `n_head = 4`, `num_layers = 2` et `output_dim = 12`.

Table I presents the results of the first scenario. The Informer model performs best, with the lowest values for MAE (0.149), RMSE (0.202), and MAPE (5.32%), as well as the highest values for R^2 (0.862) and NSE (0.862). These results show that the Informer model offers excellent water level forecasting capability. The GRU model ranks second, with performance slightly lower than that of the Informer. The Transformer model ranks third, with performance significantly lower than that of the two preceding models. Finally, the LSTM model shows the lowest performance, indicating that it fails to accurately capture water level dynamics and remains the least effective among the models studied.

TABLE I
COMPARISON OF THE PERFORMANCE OF THE MODELS STUDIED FOR SCENARIO 1

Model	MAE	RMSE	MAPE	R^2	NSE
Informer	**0.149**	**0.202**	**0.053**	**0.862**	**0.862**
GRU	0.185	0.216	0.066	0.841	0.841
Transformer	0.363	0.416	0.129	0.415	0.415
LSTM	0.544	0.639	0.194	-0.374	-0.374

For Scenario 2, the LSTM and GRU were configured with the following parameters : `input_dim = 1, hidden_dim = 256, num_layers = 4` et `output_dim = 12`. The Transformer has been configured with the following settings : `input_dim = 1, d_model = 128, n_head = 8, num_layers = 3` et `output_dim = 12`. The Informer has been configured with the following settings : `input_dim = 1, d_model = 64, n_head = 4, num_layers = 2` et `output_dim = 12`.

Table II presents the results of the second scenario. The Informer model performs best, with the lowest values for MAE (0.141), RMSE (0.184), and MAPE (5.03%), as well as the highest values for R^2 (0.885) and NSE (0.885). The GRU, Transformer, and LSTM models rank second, third, and fourth, respectively. These results show that the Informer model offers excellent water level prediction capabilities.

TABLE II
COMPARISON OF THE PERFORMANCE OF THE MODELS STUDIED FOR SCENARIO 2

Model	MAE	RMSE	MAPE	R^2	NSE
Informer	**0.141**	**0.184**	**0.050**	**0.885**	**0.885**
GRU	0.173	0.218	0.061	0.839	0.839
Transformer	0.358	0.412	0.128	0.426	0.426
LSTM	0.594	0.709	0.212	-0.694	-0.694

The figure. 6 shows the histogram of the various statistical metrics, while figure. 7 presents the radar plot of these metrics. These two figures provide a clear picture of the results of the models assessed. On the radar chart, the metrics are normalized between 0 and 1, with values closer to 1 indicating better performance. The Informer model clearly stands out by covering a larger area, delivering optimal performance across all metrics. The Informer model clearly stands out by covering a larger area, delivering optimal performance across all metrics.

These results demonstrate the Informer model's superiority in capturing the temporal dynamics of water levels, as well as its robustness compared to other models.

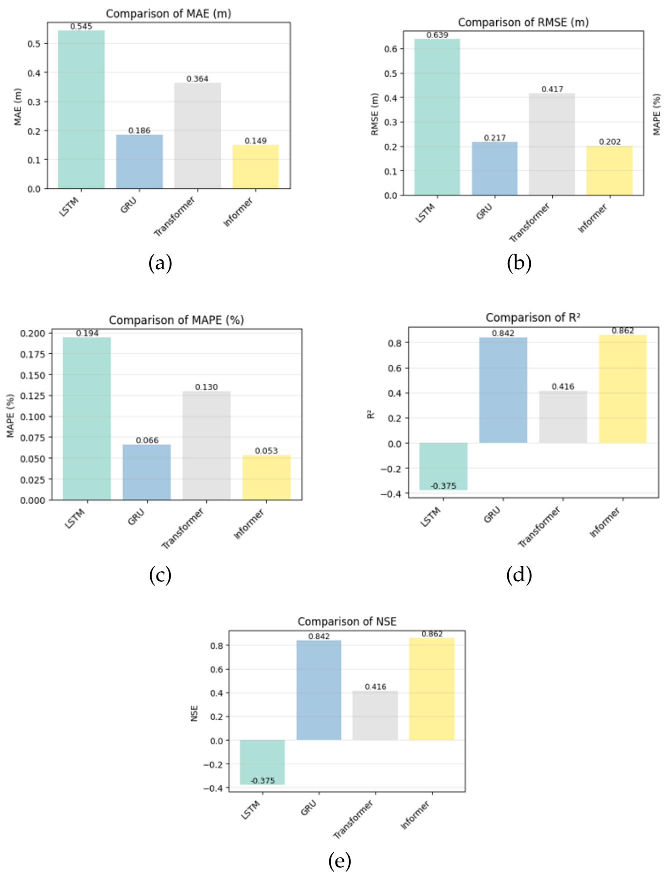


Fig. 6. Performance evaluation of LSTM, GRU, Transformer, and Informer models: (a) MAE, (b) RMSE, (c) MAPE, (d) R^2, and (e) NSE

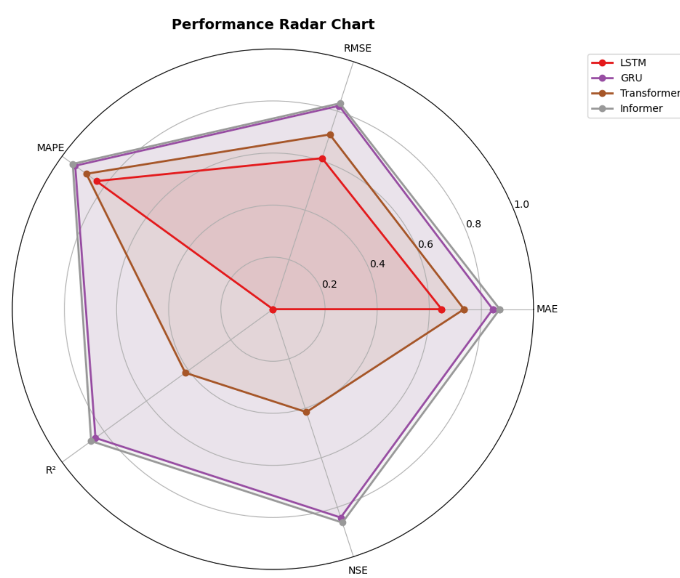


Fig. 7. Radar diagram of MAE, RMSE, MAPE, R^2 and NSE metrics for LSTM, GRU, Transformer and Informer models.

V. Conclusion

In this study, two deep learning models based on recurrent architectures—namely LSTM and GRU—as well as two models based on the Transformer architecture—namely Transformer and Informer—are presented. These models were used to forecast water levels in the Lake Chad basin for the period 2026–2050. Historical time-series data on water levels, covering the period 1960–2025, were provided by the National Meteorological Agency of Chad (ANAM-Chad). An experiment was conducted to forecast the water level of Lake Chad up to the year 2050. The models were then compared and evaluated using several statistical metrics, namely the MAE, RMSE, MAPE, the coefficient of determination (R^2), and the Nash–Sutcliffe coefficient (NSE). The results were analyzed under two scenarios in order to compare the performance of these deep learning models. Models based on attention mechanisms have proven to be more effective for forecasting hydrological time series, particularly for long sequences, and generally outperform recurrent models. For future work, the performance of deep learning models could be improved by incorporating additional meteorological variables and combining multiple models to obtain more robust forecasts. It would also be useful to test these models on other lake basins in order to assess their generalizability across different hydrological contexts.

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