Application of Deep Learning Models for Groundwater Data Analysis: A Comparative Study of CNN (Conv1D), SimpleRNN, and Gated Recurrent Unit (GRU) Models

Trong, N., G.,[1,2] Thanh, P., T.,[3*] Tinh, L., D.,[1] Thao, N., B.[4] and Elshewy, M. A.[5]
[1]Faculty of Geomatics and Land Administration, Hanoi University of Mining and Geology, No. 18 Pho Vien, Duc Thang, Bac Tu Liem, Hanoi 10000, Vietnam
E-mail: nguyengiatrong@humg.edu.vn, leductinh@humg.edu.vn
[2]Geodesy and Environment Research Group, Hanoi University of Mining and Geology, Duc Thang, Bac Tu Liem, Hanoi 10000, Vietnam
[3]Vietnam National University of Forestry, Vietnam, E-mail: trungthanhphung@gmail.com*
[4]Faculty of Geosciences and Geoengineering, Hanoi University of Mining and Geology, No. 18 Pho Vien, Duc Thang, Bac Tu Liem, Hanoi 10000, Vietnam, E-mail: nguyenbachthao@humg.edu.vn
[5]Department of Civil Engineering, Faculty of Engineering, Al-Azhar University, Cairo, Egypt
E-mail: MohamadElshewy.2214@azhar.edu.eg
*Corresponding Author

DOI: https://doi.org/10.52939/ijg.v21i3.4001

Abstract

Groundwater is a crucial resource for managing water sustainably, but it faces challenges like overuse and changes due to human activities and climate. This study looks at how deep learning models—specifically Convolutional Neural Networks (Conv1D), Simple Recurrent Neural Networks (SimpleRNN), and Gated Recurrent Units (GRU), can be used to analyze groundwater data from three monitoring stations in Vietnam. The data comes from different areas, including urban (Hanoi), metropolitan (Ho Chi Minh City), and rural-agricultural (Kien Giang) regions, with varying time intervals and data characteristics. The models were tested using several performance metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). The results showed that the Conv1D model was the best, providing the most accurate predictions, especially when the data had moderate changes. The SimpleRNN model worked well with high-resolution data but struggled when the data was more variable or incomplete. The GRU model had limited success with data that showed significant fluctuations. This study shows that Conv1D is a strong tool for groundwater monitoring and offers useful guidance on choosing the right model based on the data. It also suggests that improving data handling and adding more relevant features could help further improve predictions.

Keywords: CNN(Conv1D), Groundwater, GRU, SimpleRNN, Time-series Analysis

1. Introduction

Groundwater is an indispensable resource, serving as a primary source of water for domestic, agricultural, and industrial purposes, particularly in regions with limited surface water availability. According to Todd and May [1], groundwater accounts for approximately 30% of the Earth's total freshwater, making it a critical component of the global hydrological cycle. It supports ecosystems by maintaining water levels in wetlands and rivers, helps mitigate soil erosion, and plays a pivotal role in sustainable agricultural practices. In Vietnam, groundwater is the primary source of freshwater for millions of residents across rural and urban areas, with the Mekong Delta region being particularly reliant on this resource due to its geographic and climatic conditions [2]. However, the over-extraction and mismanagement of groundwater pose significant risks, including resource depletion, subsidence, and saltwater intrusion, making sustainable management and protection of groundwater essential for ensuring long-term water security.

Advances in computational technologies have enabled the application of data-driven models (DDMs) to address challenges in groundwater resource management. These models utilize machine learning (ML) techniques to analyze complex datasets, identify trends, and improve the predictive accuracy of traditional hydrological models.

For instance, one study [3] demonstrated the effectiveness of DDMs in reducing root mean square error (RMSE) by 82% for temporal predictions, 60% for spatial predictions, and 48% for spatiotemporal predictions, thereby improving the reliability of groundwater flow models. Integrating machine learning into groundwater analysis has yielded significant insights. An ensemble framework was introduced [4], combining spectral analysis, machine learning algorithms, and uncertainty quantification to predict groundwater level changes. When applied to the High Plains Aquifer (HPA) and Mississippi River Valley Aquifer (MRVA), the framework identified irrigation demand as the most significant influencing factor. With prediction accuracies exceeding 80% for most wells and cumulative errors under 2 meters across validation datasets from 2003 to 2012, the study demonstrated the robustness of ensemble approaches in managing groundwater resources.

Similarly, GIS-based statistical models have been applied to estimate groundwater contamination levels, such as nitrate concentrations, in compliance with environmental directives. Multiple machine learning algorithms, including Random Forest (RF), Boosted Regression Trees (BRT), and Multivariate Linear Regression (MLR), have been evaluated [5] to predict nitrate levels using spatial environmental indicators, with the RF model proving most effective. Hydrogeological characteristics, agricultural land ratios, and nitrogen balance were identified as key predictors. Machine learning techniques have also demonstrated strong performance in forecasting groundwater availability and quality. The use of automated feature selection and regression algorithms has been explored [6], where support vector regression (SVR) significantly outperformed other methods by minimizing RMSE and mean absolute error (MAE). Additionally, incorporating global features through Gaussian Mixture Models further improved prediction accuracy.

Artificial intelligence (AI) models have been employed to predict irrigation water quality. Ensemble methods, including Adaboost and Random Forest, have been employed [7] to estimate water quality indicators such as TDS (Total Dissolved Solid), SAR (Sodium Adsorption Ratio), and MAR (Magnesium Adsorption Ratio) using input variables like electrical conductivity (EC), pH, and temperature. While Artificial Neural Networks (ANN) and Support Vector Regression (SVR) produced generalized results, the ensemble approaches demonstrated higher prediction accuracy and greater robustness against input variability.

Groundwater extraction has also been modeled using integrated datasets from remote sensing and meteorological observations. Multi-temporal satellite data has been utilized [8] to estimate groundwater withdrawals. The combination of machine learning and water balance components yielded a highly accurate model, with R^2 values of approximately 0.99 and 0.93 for the training and testing datasets, respectively, showcasing the potential of hybrid approaches. Other studies have focused on groundwater quality and its influencing factors. BRT and RF models have been used to predict groundwater hardness using environmental and geospatial data. For instance, the authors in study [9] analyzed 135 monitoring wells, finding that proximity to rivers, groundwater depth, and elevation were critical determinants of water hardness, particularly in low-lying regions. Long-term forecasting of groundwater levels has been achieved using remote sensing and machine learning methods. RF was employed to analyze climate and Landsat data for groundwater-dependent ecosystems (GDEs) in California, revealing that 44% of GDEs experienced groundwater level declines between 1985 and 2019 [10]. This decline, especially after 2003, poses significant risks to ecosystems, emphasizing the urgent need for proactive groundwater management strategies.

GRACE (Gravity Recovery and Climate Experiment) satellite data was integrated with ML algorithms to predict groundwater level anomalies (GWLA) in the Indo-Gangetic Basin, demonstrating high accuracy for shallow monitoring wells, though performance declined for deeper wells due to excessive groundwater extraction [11]. Machine learning models have been used for groundwater potential mapping in semi-arid and mountainous regions, with RF, Logistic Regression (LR), Decision Trees (DT), and Artificial Neural Networks (ANN) effectively identifying groundwater sources [12]. Through the analysis of 117 previously published studies, the authors [13] demonstrated that ML methods, particularly RF, outperformed traditional mathematical models in groundwater level forecasting. Groundwater quality modeling has also advanced with the application of deep learning (DL) techniques. Machine learning models have been comprehensively evaluated for groundwater quality prediction, with ANN highlighted as the most widely used model [14]. Once again, deep learning models have been demonstrated to outperform traditional machine learning approaches in groundwater quality forecasting [15]. The RF and XGBoost models were utilized by the authors in study [16], exhibiting superior data analysis performance.

Recent advancements in AI have led to the development of automated ML approaches for groundwater modeling. Groundwater level forecasting methods from 2010 to 2020 were analyzed and synthesized by [17], leading to recommendations for the use of AI models to improve accuracy. Based on a comparative analysis of groundwater data using various machine learning models, the authors [18] concluded that the Gaussian Process Regression (GPR) model provided the best forecasting performance. The AutoML-GWL (Automated Machine Learning for Groundwater Level Prediction) framework was applied by [19], utilizing Bayesian optimization for hyperparameter tuning, achieving an RMSE of 1.22 and R = 0.90, outperforming traditional models. Machine learning has also been applied in groundwater pollution prediction. ML models were used to forecast fluoride contamination, with the Extreme Learning Machine (ELM) model achieving $R^2 = 0.921$, outperforming Multi-Layer Perceptron (MLP) and SVM models [20]. In Vietnam, Cường and Thắng [21] applied ML models for groundwater quality prediction, demonstrating that the Cubist model achieved the highest accuracy, with $R^2 = 98.8\%$ for the training set and 96% for the testing set.

Deep learning has further enhanced geospatial and time-series groundwater data analysis. Convolutional Neural Networks (CNNs), particularly Conv1D architectures, have gained attention for their ability to extract spatial-temporal patterns from groundwater datasets. Deep learning models have been confirmed to be superior in analyzing time-series data, particularly in hydrological applications [22]. The CNN (Conv1D) model was utilized by [23] for flood risk zoning based on geospatial data, achieving an accuracy of up to 90.7%. Furthermore, the CNN (Conv1D) model has also demonstrated outstanding performance in analyzing GNSS time-series data, with an R-squared value of 99.7% [24].

Recurrent Neural Networks (RNNs), including SimpleRNN and GRU, have also been explored for groundwater prediction. The SimpleRNN model has demonstrated its ability to capture temporal dependencies, making it suitable for long-term time-series forecasting [25]. However, its limitations in retaining long-term dependencies have been addressed by more advanced architectures like LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit). RNN, LSTM, and GRU models have been used for multi-class electroencephalography (EEG) signal classification, with experimental results showing that the GRU model performs efficiently in sequential data processing [26]. Given the growing demand for accurate groundwater monitoring, this study aims to compare the performance of deep learning models - CNN(Conv1D), SimpleRNN, and GRU - for groundwater time-series forecasting in Vietnam. Using data from Hanoi (urban), Ho Chi Minh City (metropolitan), and Kien Giang (rural-agricultural) monitoring stations, the models will be evaluated based on Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). By identifying the most effective model for groundwater prediction, this research seeks to enhance data-driven decision-making in groundwater management and contribute to sustainable water resource planning.

This study builds on these advancements, applying CNN (Conv1D), SimpleRNN, and GRU models to groundwater observation data collected from three monitoring stations in Vietnam. The aim is to evaluate the suitability and performance of these models in predicting groundwater levels, with implications for improving water resource management and forecasting accuracy. These models were selected because they have demonstrated their advantages in processing time-series data, such as GNSS data [24], tidal observation data [27], and agricultural price forecasting [28].

2. Data and Methodology

2.1 Investigation and Data Collection Area

The dataset utilized in this research was obtained from the Southern Water Resources Planning and Investigation Federation under the National Center for Water Resources Planning and Investigation (NAWAPI). The data encompasses groundwater observations from three monitoring wells situated in distinct geographic regions of Vietnam: Hanoi, Ho Chi Minh City, and Kien Giang.

Specifically:

1. Station Q55M1 (Hanoi): Positioned in the northern region of Vietnam, this station captures data in an urban environment with significant population density and industrial activity. Its location provides insights into groundwater dynamics influenced by urbanization and local climatic patterns.

2. Station Q080810 (Ho Chi Minh City): Situated in the southern part of Vietnam, this station monitors groundwater levels in a major metropolitan area characterized by rapid economic growth and high-water demand. The data from this station is crucial for understanding groundwater fluctuations in highly urbanized settings.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

3. Station Q40101T (Kien Giang): Located in the Mekong Delta, this station represents a rural and agriculturally intensive area. It offers a unique perspective on groundwater behavior in regions heavily influenced by irrigation practices and seasonal hydrological changes.

The data from these three stations, detailed in Table 1, serves as the foundation for evaluating the performance of deep learning models in analyzing groundwater levels across varying temporal and spatial conditions. Figure 1 illustrates the geographic positioning of these stations, highlighting their importance in capturing groundwater variability across urban, peri-urban, and rural landscapes in Vietnam.

2.2 Methodology

2.2.1 Model descriptions and evaluation metrics

The Conv1D model, a specialized variant of Convolutional Neural Networks (CNN), is designed specifically for analyzing one-dimensional sequential data, such as time-series datasets. Unlike traditional convolutional architectures optimized for two-dimensional spatial inputs, Conv1D focuses on detecting temporal patterns and trends within sequential data. By applying convolutional operations along the time axis, it effectively identifies features such as recurring patterns or abrupt changes. This capability has made Conv1D highly effective in various domains, including predictive modeling, signal processing, and audio analysis. The architecture typically includes layers for feature extraction, dimensionality reduction through pooling, and final predictions via fully connected layers. Compared to Recurrent Neural Networks (RNNs), Conv1D models achieve a balance of efficiency and reliability by capturing temporal relationships with a relatively smaller parameter count, making them computationally efficient for time-series tasks. The Gated Recurrent Unit (GRU) is a type of RNN explicitly designed for sequential data by capturing temporal dependencies over extended timeframes.

Table 1: Information about monitoring data

TT	Station name	Latitude (degree)	Longitude (degree)	Elevation (m)	Start time / Stop time	Interval
1	Q55M1	21.10	105.72	8.14	01/01/2020 01/01/2023	hourly
2	Q808010	10.78	106.51	1.23	08/01/1992 02/27/2016	daily with missing data days
3	Q40101T	9.88	105.16	2.00	03/01/2000 12/01/2016	daily

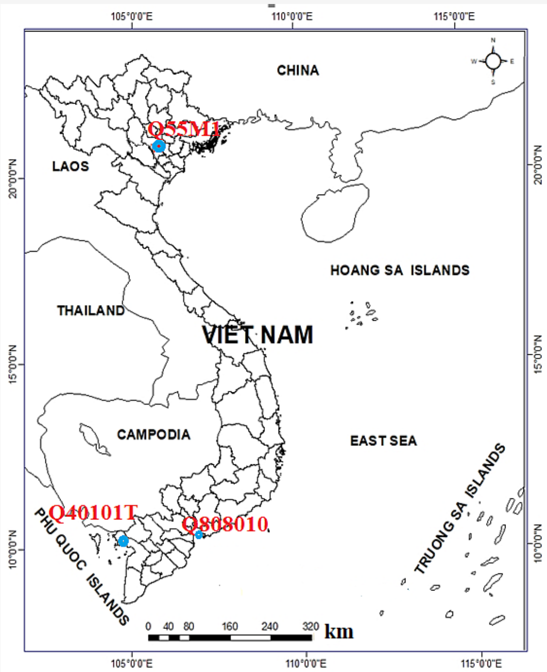

Figure 1: Locations of groundwater observation wells in Vietnam

Unlike Conv1D, which analyzes patterns within fixed-size temporal windows, GRUs are better suited for tasks requiring memory of long-term dependencies. GRUs achieve this through gating mechanisms, including update and reset gates, which regulate information flow and mitigate the vanishing gradient problem commonly observed in traditional RNNs. These features make GRUs highly effective for applications such as time-series forecasting, speech processing, and natural language understanding. While Conv1D models are computationally faster and excel at localized pattern detection, GRUs provide an advantage in scenarios where sequential context plays a critical role. The Simple Recurrent Neural Network (SimpleRNN) represents an earlier generation of RNN models used to analyze sequential data, including time series. It processes data sequentially by maintaining a hidden state that evolves with each time step, enabling the capture of short-term dependencies. However, its effectiveness diminishes for long-term dependencies due to the vanishing gradient problem, limiting its ability to model complex temporal patterns. Despite these limitations, SimpleRNN serves as a foundational model for time-series analysis, particularly in tasks with minimal temporal dependencies. It is computationally lightweight and straightforward to implement, though it is often replaced by more advanced architectures like GRU and LSTM for improved performance.

2.2.2 Implementation details

In this study, all three models - Conv1D, GRU, and SimpleRNN - were implemented with a single hidden layer comprising 64 filters. The models employed the Adam optimization algorithm and Mean Squared Error (MSE) as the loss function. Adam combines the advantages of Gradient Descent and Momentum techniques, offering adaptive learning rates and reducing the likelihood of converging to local minima, which is especially beneficial for complex time-series datasets. MSE evaluates the accuracy of predictions by measuring the squared error between actual and predicted values, making it a suitable metric for regression and time-series tasks.

2.2.3 Performance evaluation metrics

To assess the effectiveness of the models in groundwater data analysis, the following metrics were used:

1. Mean Squared Error (MSE): Measures the average squared difference between observed and predicted values. Lower MSE values indicate better model performance.
2. Root Mean Squared Error (RMSE): As the square root of MSE, this metric provides error measurements in the same units as the target variable, making it more interpretable, especially when penalizing larger errors.
3. Mean Absolute Error (MAE): Computes the average magnitude of prediction errors without considering direction. Unlike MSE, MAE is less sensitive to outliers and offers straightforward interpretability.
4. R-squared (R^2): Indicates the proportion of variance in the dependent variable explained by the model. R^2 values closer to 1 signify a better fit, reflecting high predictive accuracy.

2.2.4 Development tools

The computational framework for this study was implemented in Python, leveraging powerful libraries such as *pandas* for data manipulation, *numpy* for numerical computations, and *tensorflow* for deep learning model development [29] and [30]. These tools facilitated efficient data processing, model training, and evaluation, enabling robust analysis of the groundwater datasets. The methodology employed for analyzing groundwater observation data in this study is systematically illustrated in Figure 2.

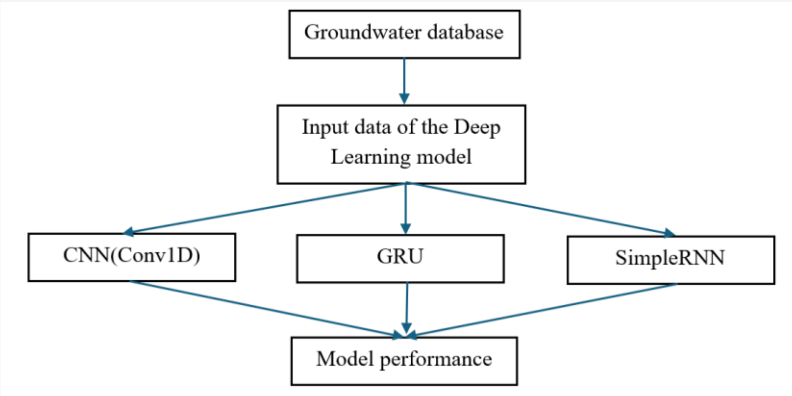

Figure 2: Flowchart of the groundwater data analysis procedure

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

This diagram provides a comprehensive overview of the step-by-step approach adopted to process and evaluate the groundwater datasets. The input data for the deep learning models consists of groundwater observation data recorded over time. This data is stored in a .csv file with two columns: time and water level. Before being fed into the models, the dataset undergoes preprocessing, including normalization and partitioning into training, validation, and testing sets. This ensures that the models can learn patterns effectively while avoiding overfitting.

Once the data is prepared, it is used as input for three different deep learning architectures: CNN (Conv1D), GRU, and SimpleRNN. The CNN (Conv1D) model extracts spatial features from the time-series data using one-dimensional convolutional filters. This method helps capture local patterns within the sequence. The GRU (Gated Recurrent Unit) model processes the data sequentially and retains important information over time through its gating mechanism, making it effective for handling long-term dependencies. The SimpleRNN model, a basic recurrent neural network, also processes sequential data but is more prone to issues like vanishing gradients, which may affect its performance compared to GRU.

The final step involves evaluating model performance. The predicted values from CNN, GRU, and SimpleRNN are compared against actual groundwater levels to assess accuracy. Standard performance metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used for this evaluation. By analyzing these results, the most suitable model for groundwater level prediction can be identified. This structured data flow ensures a systematic approach to modeling groundwater levels, providing valuable insights into the effectiveness of different deep learning techniques for time-series forecasting.

3. Results and Discussion

The performance evaluation of the SimpleRNN, CNN(Conv1D), and GRU models for groundwater level prediction across three distinct monitoring stations in Vietnam (Q55M1, Q080810, and Q40101T) reveals critical insights into their respective predictive accuracies and limitations. This section provides a detailed analysis of the results obtained for each model, highlighting their suitability, strengths, and challenges when applied to different datasets.

3.1 Analysis with the SimpleRNN Model

The performance metrics for the SimpleRNN model, summarized in Table 2, show strong agreement between predicted and observed values, with R^2 values nearing 100% across all stations. However, variations in error metrics (MSE, RMSE, and MAE) highlight a station-dependent performance gradient:

- Station Q55M1: The SimpleRNN model achieved an RMSE of 0.07 mm and an MAE of 0.06 mm, reflecting near-perfect accuracy. The high data resolution (hourly measurements over three years) at this station likely contributed to the model's superior performance by providing a rich dataset for temporal learning.
- Station Q080810: The RMSE increased to 2.58 mm, and the MAE to 2.28 mm, indicative of slightly reduced accuracy. The daily data collection frequency, along with missing data points, may have introduced challenges in capturing detailed temporal patterns, reducing the model's precision.
- Station Q40101T: The model exhibited the highest error metrics, with an RMSE of 4.23 mm and an MAE of 2.57 mm. The lower accuracy is attributed to the limited dataset size and the significant variability in groundwater levels at this station, which posed challenges for the SimpleRNN's capability to generalize.

The evaluation metrics in the table indicate the model's accuracy across different observation stations. The MSE values show that the prediction error is minimal for Q55M1 (0.00 mm) and increases for Q808010 (6.67 mm) and Q40101T (17.89 mm), suggesting slightly larger deviations at these stations. The RMSE values, which measure the standard deviation of prediction errors, follow a similar trend, with Q55M1 having the lowest error (0.07 mm) and Q40101T the highest (4.23 mm). The MAE values indicate that, on average, the absolute difference between predicted and actual values is smallest for Q55M1 (0.06 mm) and largest for Q40101T (2.57 mm), but all values remain relatively low. The R^2 values are close to 1 for all stations, ranging from 0.9998 to 1.00, demonstrating that the model fits the observed data extremely well and provides highly accurate predictions.

Visual analysis (Figure 3) demonstrates that while the model captured the general trends in groundwater fluctuations, deviations between observed and predicted values were more pronounced in datasets with higher temporal variability, as seen in station Q40101T.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

Table 2: Performance statistics of the SimpleRNN model

Station	MSE (mm)	RMSE (mm)	MAE (mm)	R^2
Q55M1	0.00	0.07	0.06	1.00
Q808010	6.67	2.58	2.28	1.00
Q40101T	17.89	4.23	2.57	0.99

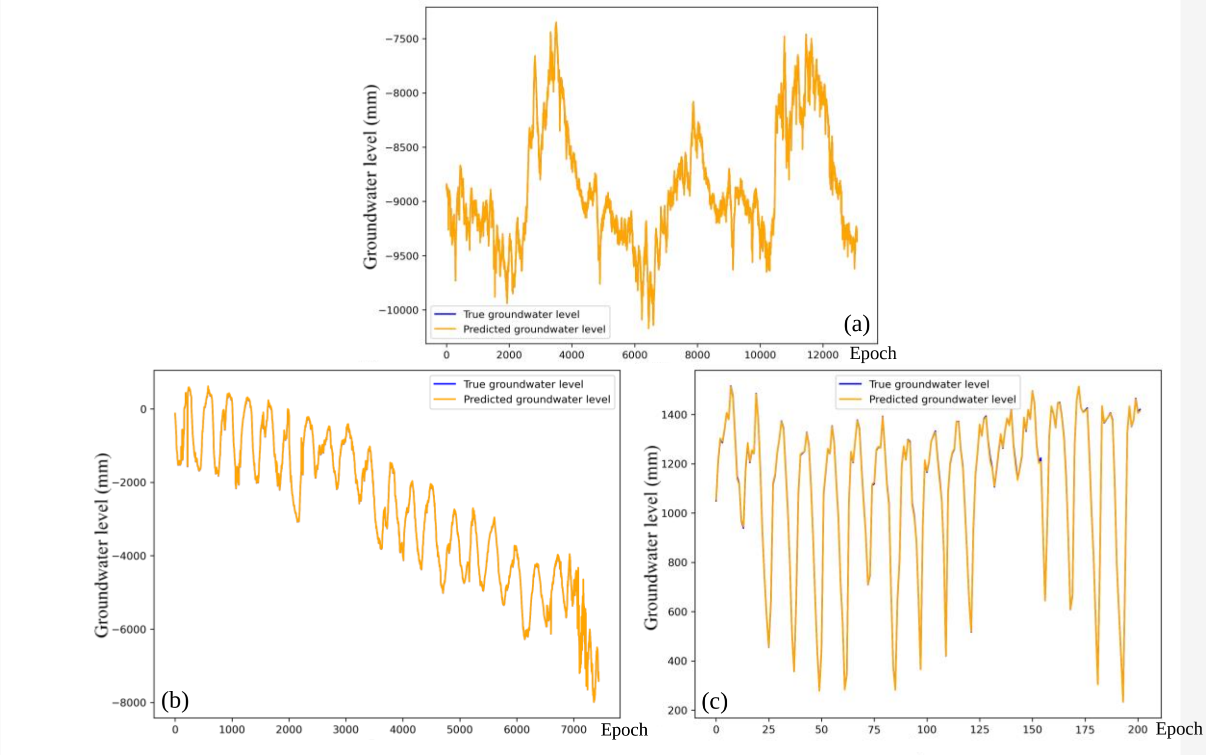

Figure 3: SimpleRNN predicted and actual groundwater level at observation stations: (a) Q55M1 (b) Q808010 (c) Q40101T

From the above figure, it can be observed that the predicted values using the SimpleRNN model are very close to the actual values at the groundwater observation points. The performance of the SimpleRNN model is the weakest when analyzing data collected at station Q40101T, leading to noticeable differences between the predicted and actual values at this station. This discrepancy is visually evident as the predicted values can be distinguished by their color on the graph. The three-dimensional plots (Figure 4) provide further confirmation of this trend, highlighting the need for more advanced models to address such variability.

3.2 Analysis with the CNN (Conv1D) Model

The prediction performance of the CNN(Conv1D) model for the data from the three stations is shown in Table 3. The CNN(Conv1D) model outperformed the SimpleRNN model in most performance metrics, as detailed in Table 3. Its architecture, designed for extracting temporal features in sequential data, proved particularly effective for the groundwater datasets:

- Station Q55M1: The CNN(Conv1D) model achieved an RMSE of 0.05 mm and an MAE of 0.03 mm, outperforming the SimpleRNN. Its ability to detect fine-grained temporal patterns likely contributed to this exceptional accuracy.
- Station Q080810: The model exhibited a substantial improvement, reducing the RMSE from 2.58 mm (SimpleRNN) to 0.06 mm and the MAE from 2.28 mm to 0.04 mm. This significant enhancement underscores the CNN's robustness in handling datasets with lower resolution and missing values.
- Station Q40101T: Despite the challenges posed by high variability, the CNN(Conv1D) model achieved an RMSE of 2.88 mm and an MAE of 2.0 mm, a marked improvement over the SimpleRNN's performance. The model's capability to learn localized patterns even in datasets with significant fluctuations is evident.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

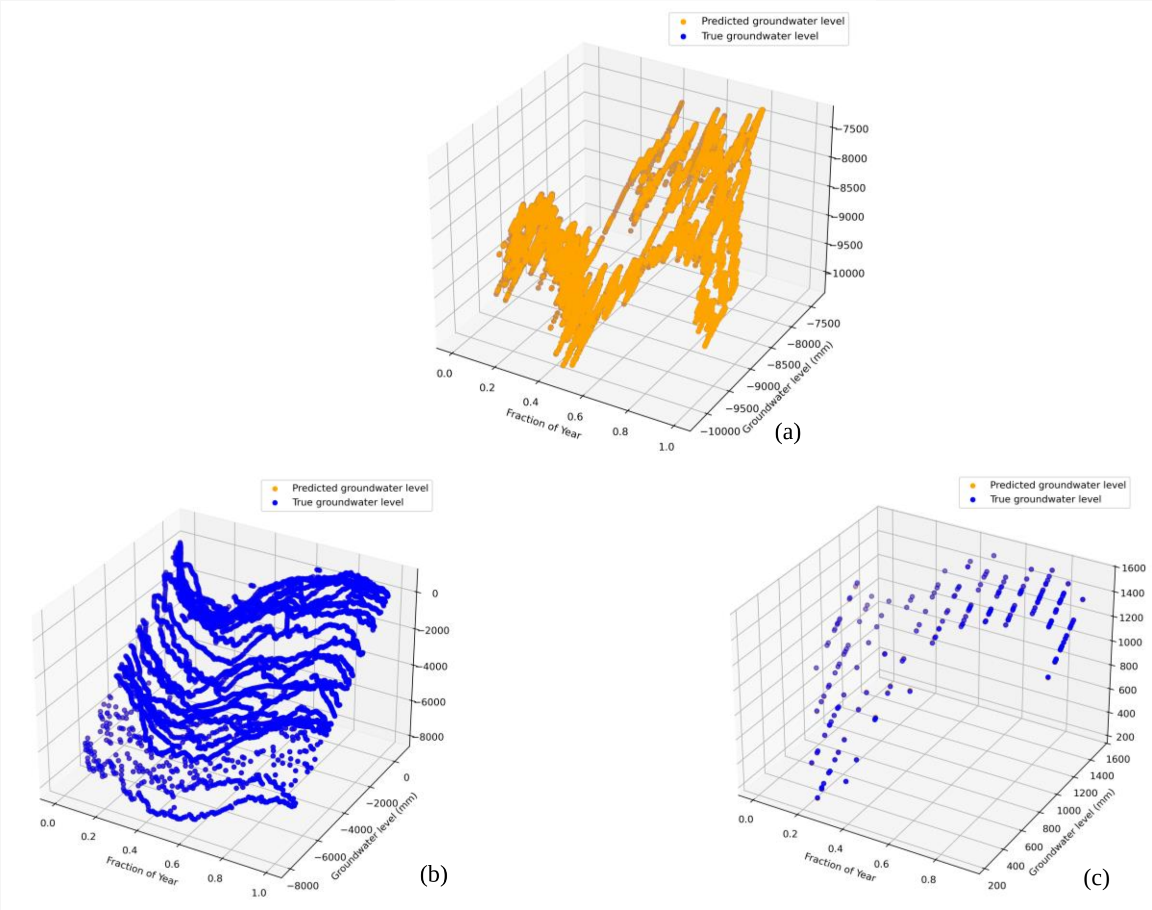

Figure 4: 3D projection of groundwater level using SimpleRNN at observation stations: (a) Q55M1 (b) Q808010 (c) Q40101T

Table 3: Performance statistics of the CNN(Conv1D) model

Station	MSE (mm)	RMSE (mm)	MAE (mm)	R^2
Q55M1	0.00	0.05	0.03	1.00
Q808010	0.00	0.06	0.04	1.00
Q40101T	8.30	2.88	2.0	0.99

Table 3, the results indicate a further reduction in prediction errors compared to the first table. Both MSE and RMSE values for Q55M1 and Q808010 are extremely low (0.00 mm and 0.05–0.06 mm, respectively), suggesting near-perfect predictions at these stations. The MAE values are also minimal, with the largest absolute error at Q40101T (2.0 mm), which remains relatively low. The R^2 values remain consistently close to 1 (ranging from 0.9999 to 1.00), reinforcing the high accuracy of the model. However, Q40101T still shows slightly higher errors compared to the other stations, as reflected in its MSE (8.30 mm) and RMSE (2.88 mm), though these values indicate improved performance relative to the Table 2. The predicted versus observed plots (Figure 5) illustrate the CNN(Conv1D)'s superior alignment with the observed data trends. The results suggest that this model is particularly suitable for groundwater monitoring tasks, especially in environments with moderate to high data variability.

From the charts and statistical data in Tables 2 and 3, it can be observed that, in addition to the small amount of input data, one of the reasons for the lower prediction performance with data from station Q40101T is the high variability in the groundwater levels at this station. 3D plots representing the predicted groundwater levels of stations Q55M1, Q808010, and Q40101T using the CNN (Conv1D) model are shown in Figure 6.

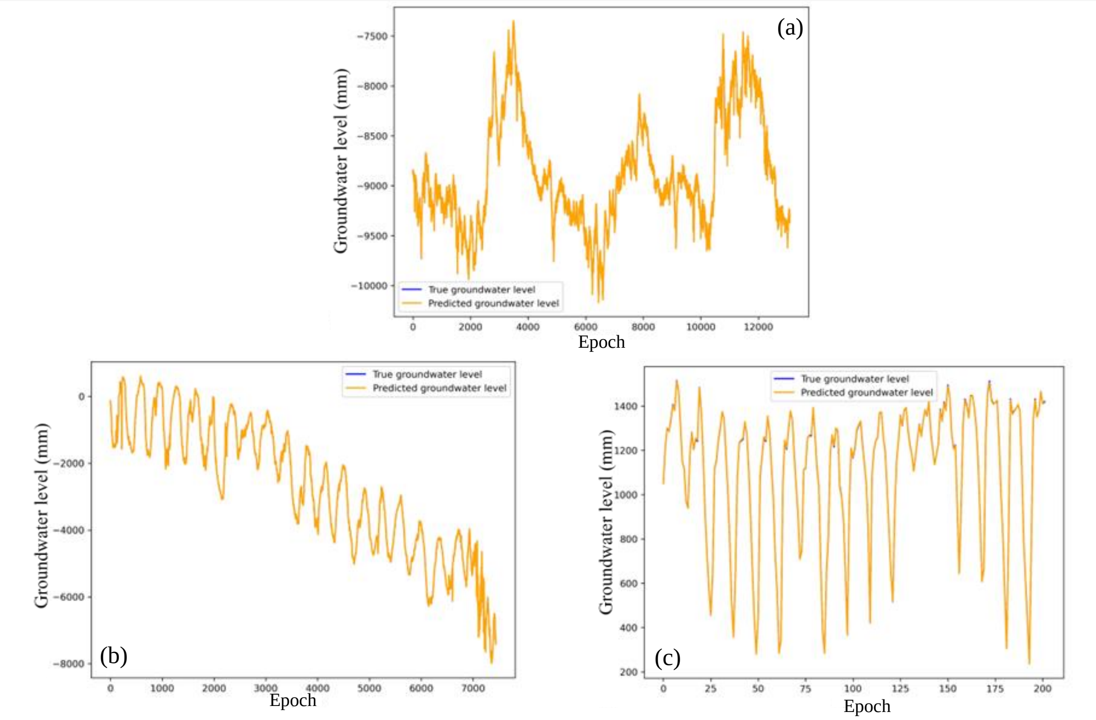

Figure 5: CNN(Conv1D) predicted and actual values at observation stations:
(a) Q55M1 (b) Q808010 (c) Q40101T

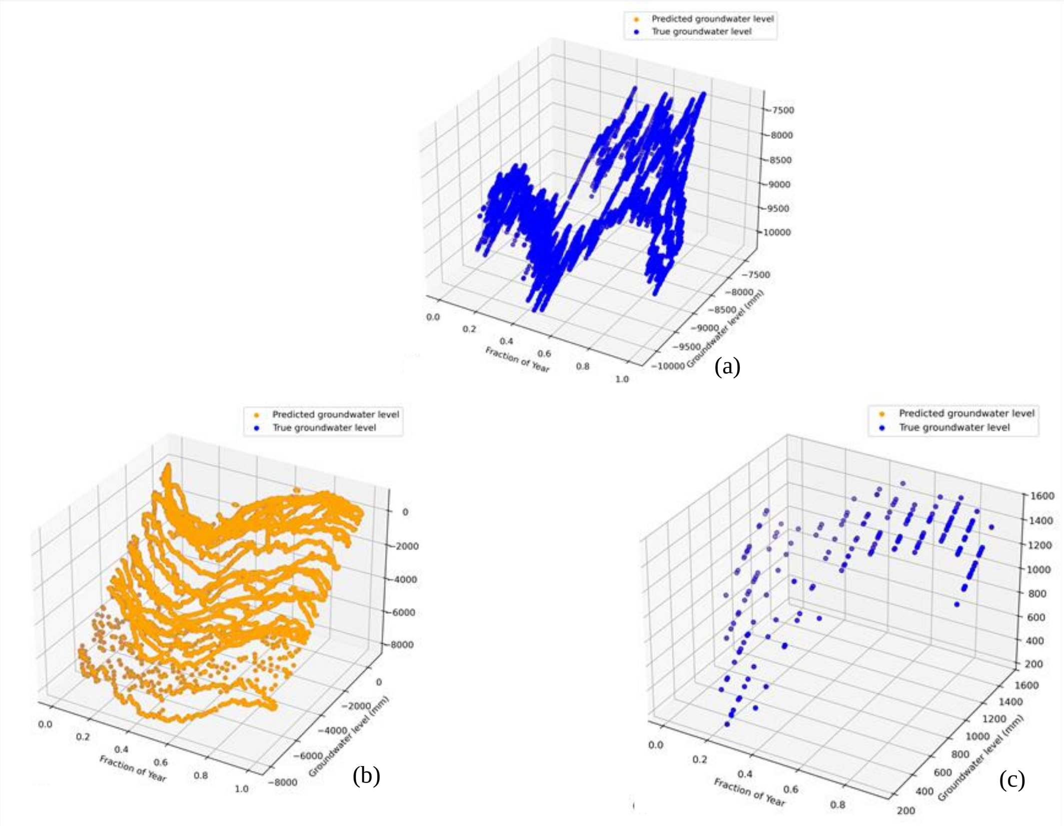

Figure 6: 3D projection of groundwater level using CNN(Conv1D) at observation stations:
(a) Q55M1 (b) Q808010 (c) Q40101T

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

From Figure 6, it can be observed that the predicted value curve (especially for the data from station Q40101T) obtained using the CNN (Conv1D) model is closer to the actual value curve. This is entirely consistent with the fact that the forecasting performance of the CNN (Conv1D) model is better than that of the SimpleRNN model.

3.3 Analysis with the GRU Model

The results of the analysis of groundwater monitoring data from the three stations Q55M1, Q080810, Q40101T using the GRU model with 128 filters are provided in Table 4. The GRU model's performance, summarized in Table 4, was less consistent compared to the CNN(Conv1D) and SimpleRNN models. While it effectively captured general trends, its predictive accuracy varied across stations:

- Station Q55M1: The GRU model yielded an RMSE of 1.35 mm and an MAE of 1.26 mm. Although the R^2 value was high, the error metrics were significantly higher than those of the CNN and SimpleRNN models, indicating a relative inefficiency in leveraging high-resolution datasets.

- Station Q080810: The GRU model demonstrated comparable performance to the SimpleRNN, with an RMSE of 2.57 mm and an MAE of 2.36 mm. This indicates that the GRU struggled with the same challenges faced by the SimpleRNN model, particularly data sparsity and missing values.

- Station Q40101T: The GRU model's RMSE increased to 7.39 mm, and its MAE to 5.82 mm, the highest among the models tested. This indicates significant limitations in handling datasets with extreme variability and limited size.

From Table 4, it can be seen that the prediction errors increase significantly, particularly for Q40101T. The MSE (54.58 mm) and RMSE (7.39 mm) are notably higher than in previous tables, suggesting greater deviations between predicted and actual values at this station. Similarly, MAE for Q40101T reaches 5.82 mm, indicating larger average errors. In contrast, Q55M1 and Q808010 still maintain relatively low error values, though they are slightly higher than those in the previous tables. Despite these variations, the R^2 values remain at or near 1.00, demonstrating that the model still effectively captures the overall trends in groundwater levels, even with increased prediction errors at certain stations. Figure 7 (two-dimensional plots) and Figure 8 (three-dimensional visualizations) reveal that while the GRU captured broad trends, it struggled with fine-grained predictions, particularly in highly variable datasets. The GRU model performs the worst compared to the SimpleRNN and CNN (Conv1D) models. As a result, the predicted groundwater level curve shows a more significant difference from the actual value curve.

3.4 Independent Forecast Results

To rigorously evaluate the performance of models in groundwater data analysis, groundwater level forecasting was conducted for future timeframes. Specifically, observational data from station Q40101T, starting on July 1, 2016, was withheld from the model training process. This withheld data was then utilized as a validation set to assess the prediction accuracy for the target dates of July 1, 2016, and August 1, 2016. The model development leveraged the complete dataset, excluding the validation period, to ensure robust training. The forecasting outcomes generated by the CNN (Conv1D), GRU, and SimpleRNN models are summarized in Table 5, while Table 6 provides a detailed comparison of the deviations in predicted groundwater levels for the specified future dates.

Table 4: Results of groundwater monitoring data analysis at 3 stations using the GRU model with 128 filters

Station	MSE (mm)	RMSE (mm)	MAE (mm)	R^2
Q55M1	1.83	1.35	1.26	1.0
Q808010	6.58	2.57	2.36	1.0
Q40101T	54.58	7.39	5.82	0.999

Table 5: Predicted future groundwater levels for station Q40101T

Time	True groundwater level value (m)	Predicted groundwater level values (m)		
		SimpleRNN	CNN (conv1D)	GRU
July 1, 2016	1.432	1.412	1.427	1.383
August 1, 2016	1.351	1.374	1.291	1.300

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

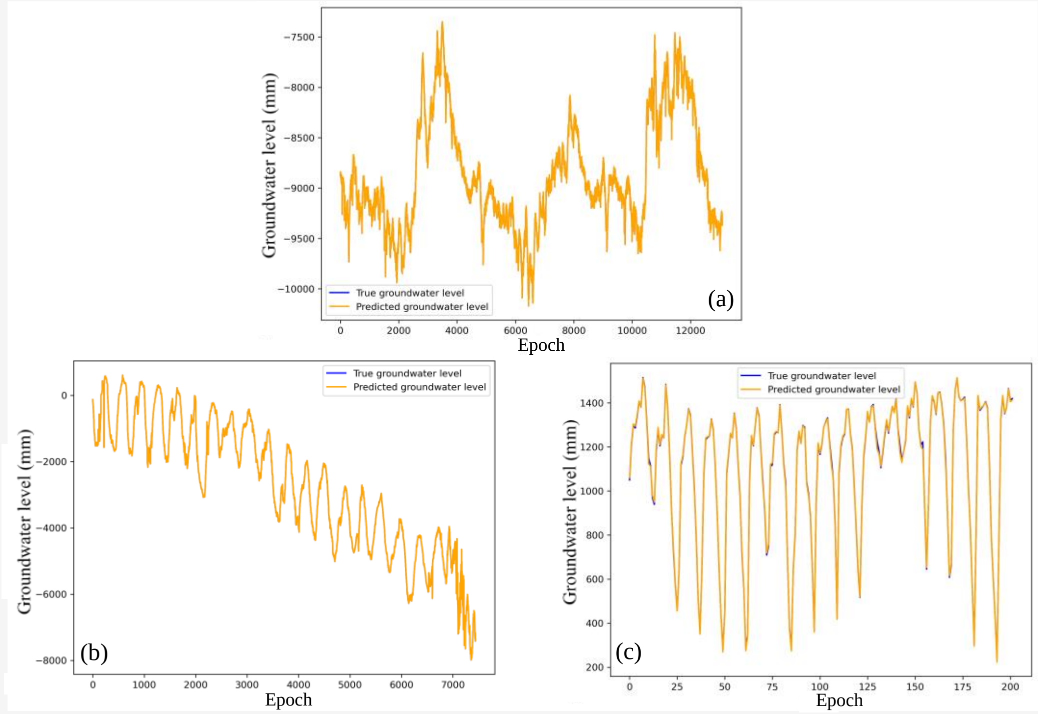

Figure 7: GRU predicted and actual values at observation stations: (a) Q55M1 (b) Q808010 (c) Q40101T

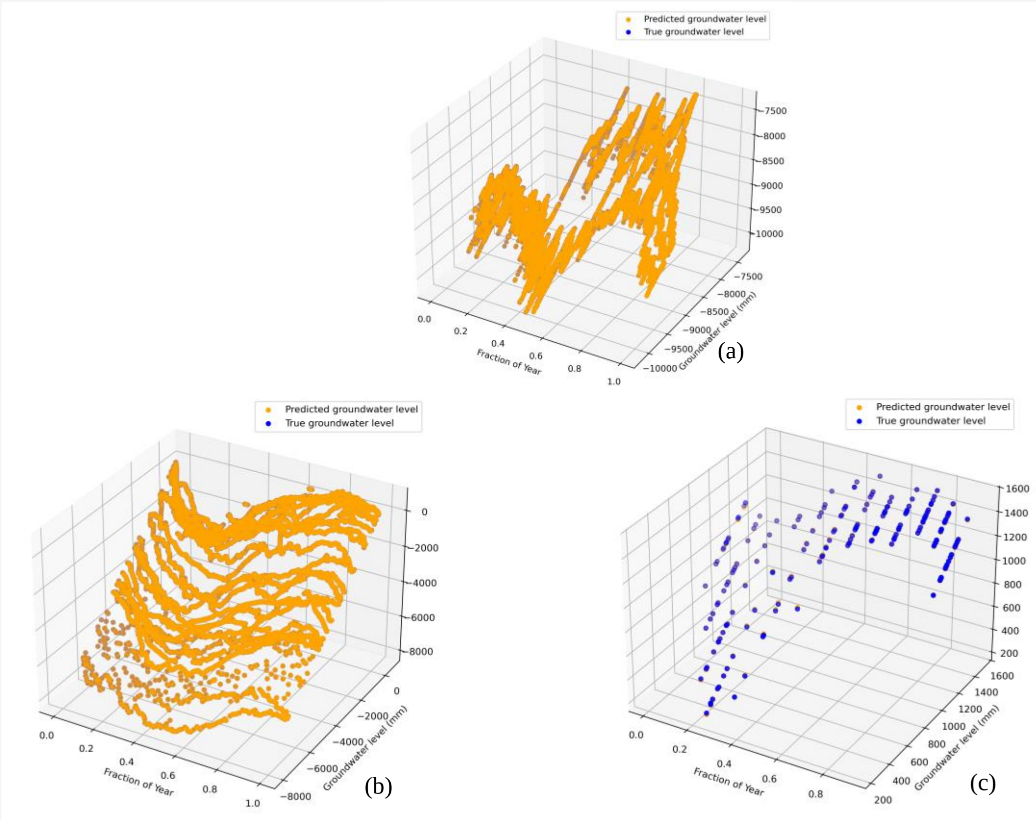

Figure 8: 3D projection of groundwater level using GRU at observation stations:
(a) Q55M1 (b) Q808010 (c) Q40101T

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

Table 6: Deviation of predicted future groundwater levels

Time	Deviation of groundwater level prediction (mm)		
	SimpleRNN	CNN (conv1D)	GRU
July 1, 2016	-20	-5	-49
August 1, 2016	23	-60	-51

Based on the table, the predicted values from the CNN (Conv1D) model are the closest to the true values, particularly on July 1, 2016, where the predicted value (1.427) is almost identical to the actual value (1.432). Similarly, for August 1, 2016, the SimpleRNN model provides a closer estimate (1.374) compared to the true value (1.351), while CNN (Conv1D) slightly underestimates the value (1.291). Among the three models, the GRU model shows the largest deviation from the actual values on both dates, especially on July 1, 2016, where it predicts 1.383 instead of 1.432. This suggests that GRU has the weakest performance in this scenario, while CNN (Conv1D) and SimpleRNN demonstrate better predictive accuracy.

The results presented in Table 6 indicate that the CNN (Conv1D) model achieves the highest accuracy for near-term groundwater level predictions, with a minimal deviation of only 5 mm for the immediate next time point. This is followed by the SimpleRNN model, which exhibits a slightly larger deviation of 20 mm, while the GRU model demonstrates the least accurate performance with a deviation of 49 mm. For predictions extending to two consecutive time points, the SimpleRNN model outperforms the others, showing the smallest deviation of 23 mm at the second time point. The GRU model ranks second in accuracy for this scenario, whereas the CNN (Conv1D) model shows the largest deviation of 6.1 cm at the second time point. Despite this, it is important to note that in practical applications, forecasted values are commonly updated using newly measured data from the preceding time point. This iterative update process enhances the overall reliability of the CNN (Conv1D) model, underscoring its effectiveness in forecasting future groundwater levels under real-world conditions.

3.5 Comparison with Similar Studies

The use of deep learning models for groundwater monitoring has gained significant attention due to their ability to analyze complex temporal patterns and produce accurate predictions. This study contributes to the field by evaluating three models - Conv1D, SimpleRNN, and GRU - for predicting groundwater levels in various regions of Vietnam. The findings extend previous research, demonstrating improvements in prediction accuracy and model adaptability. An ensemble framework that integrated machine learning with spectral analysis achieved over 80% accuracy in predicting groundwater levels in agricultural areas [4]. However, the Conv1D model in this study outperformed previous approaches, particularly in datasets with missing values or moderate variability, such as at station Q808010. The superior performance of Conv1D is attributed to its capability to capture intricate temporal patterns effectively. Other studies have employed machine learning models such as Random Forest (RF) and Support Vector Regression (SVR) for predicting groundwater quality and availability, yielding satisfactory results in certain cases but encountering difficulties with complex or time-dependent data [5][6]. In contrast, the Conv1D model demonstrated robust performance across diverse scenarios, achieving near-perfect prediction accuracy in terms of R^2 values.

High-resolution data has been identified as a crucial factor for improving prediction accuracy [6]. This study reaffirmed that the SimpleRNN model performed well with high-resolution data, such as hourly readings at station Q55M1, but struggled with lower-resolution or highly variable datasets. Similar challenges have been reported in earlier research [8]. Meanwhile, the Conv1D model maintained consistent performance across different data types, highlighting its versatility. However, datasets with missing information or substantial variability presented difficulties for all models, particularly at station Q40101T. Previous studies that utilized machine learning and remote sensing for groundwater predictions also noted that incomplete data led to decreased accuracy [10]. While the Conv1D model in this study managed these challenges better than other models, addressing data gaps through preprocessing techniques could further enhance its reliability.

Long-term groundwater level predictions have also been explored using Random Forest models [19]. However, this study found that GRU models, despite being designed for sequential pattern recognition, struggled with highly variable data. These findings emphasize the need for advanced techniques, such as hybrid approaches that integrate Conv1D with other architectures or the application of transformers, to further enhance long-term prediction accuracy. Table 7 shows a comparative analysis summarizing the main findings of recent studies and comparing them with the results of this study.

Table 7: Comparative analysis of deep learning models for groundwater prediction

Models Used	Dataset Characteristics	Performance Metrics	Key Findings	Comparison with This Study	Reference
Machine Learning (ML) + Spectral Analysis	Agricultural groundwater datasets, US	Accuracy > 80%	Identified irrigation demand as the most significant factor	Our Conv1D model achieved near-perfect accuracy ($R^2 \approx 1$), demonstrating better handling of missing data and variability	[4]
Random Forest (RF), Boosted Regression Trees (BRT), Multivariate Linear Regression (MLR)	Groundwater contamination prediction	RF performed best	Effective for contamination level estimation but struggled with time-dependent data	Conv1D outperforms in time-series forecasting but RF is better for spatial contamination mapping	[5]
Support Vector Regression (SVR), RF, Automated Feature Selection	Groundwater availability prediction	RMSE and MAE minimized with SVR	High-resolution data improves accuracy	Similar finding: Our SimpleRNN model performed well with high-resolution data at Q55M1, but struggled with variability	[6]
ML + Remote Sensing	Groundwater withdrawal estimation	$R^2 \approx 0.99$ (train), 0.93 (test)	Missing data reduced model performance	Our Conv1D model managed missing data better, achieving high accuracy even with variable data	[8]
Random Forest (RF)	Long-term groundwater level forecasting	44% decline in GDEs detected	RF is good for long-term trends but lacks fine-scale accuracy	GRU in this study performed worst, suggesting more advanced hybrid models are needed for long-term forecasting	[10]
Automated ML for Groundwater Level (AutoML-GWL)	Bayesian optimization for hyperparameters	RMSE = 1.22, R = 0.90	Outperformed traditional ML models	Our CNN (Conv1D) model performed similarly in accuracy but with simpler architecture and manual tuning	[19]

Table 7 illustrates how this research aligns with and expands upon prior studies. It highlights the strengths of the Conv1D model in handling variable and missing data, the effectiveness of SimpleRNN with high-resolution data, and the limitations of GRU in extreme variability scenarios.

4. Conclusion

This study tested three machine learning models - SimpleRNN, CNN (Conv1D), and GRU - for predicting groundwater levels at three stations in Vietnam: Q55M1, Q080810, and Q40101T. The results showed that the performance of each model varied depending on the quality and type of the data. The CNN (Conv1D) model was the most accurate, especially when there was moderate variability or missing data, like at station Q080810, where it achieved very low error rates (RMSE of 0.06 mm and MAE of 0.04 mm). This model's ability to capture detailed patterns over time made it highly effective for groundwater monitoring. The SimpleRNN model worked very well with high-resolution data, like the hourly data at station Q55M1, where it had almost perfect accuracy (RMSE of 0.07 mm and MAE of 0.06 mm). However, it struggled with data that had lower resolution or more variability, like the data from station Q40101T. The GRU model, on the other hand, showed the highest error rates across all stations, especially at Q40101T, where it had a large RMSE of 7.39 mm and an MAE of 5.82 mm. While it was good at capturing general trends, it wasn't as accurate in predicting specific values. For short-term predictions at Q40101T, the CNN (Conv1D) model provided the best predictions for the next time point, with a small error of just 5 mm. The SimpleRNN and GRU models were less accurate. However, when predicting the second time point, the SimpleRNN model performed best, with the smallest error of 2.3 cm.

This shows that different models work better at different time points, depending on the data and the prediction needs. The CNN (Conv1D) model's consistent accuracy across different datasets and its ability to handle data variability make it the best choice for long-term groundwater level forecasting.

The SimpleRNN model works well with high-resolution data, but its performance drops when the data is more variable, suggesting that improving the data or using a combination of models could help. The GRU model could be improved by adding more complexity or using better features for datasets with complex patterns. Improving data quality through methods like filling in missing data or adding extra environmental data could also improve predictions for all models. Future research could explore more advanced deep learning techniques, such as transformers, to improve long-term predictions. In conclusion, the CNN (Conv1D) model stands out as the best option for different groundwater monitoring scenarios, but the choice of model should depend on the characteristics of the data and the specific forecasting needs.

5. Recommendations

Based on the obtained results, the groundwater data analysis method proposed in this paper can be effectively applied in practice. Although the experimental results in this study demonstrate the high performance of the artificial intelligence model in analyzing groundwater monitoring data, further research is needed to optimize the model for different cases. Additionally, analysis using a combination of various types of input data, alongside groundwater data, should be conducted to enhance its applicability in studies on natural hazards and climate change.

Acknowledgements

This work was financially supported by the Ministry of Natural Research and Environment in Vietnam under grant number TNMT.ĐL.2025.06.03

References

[1] Todd, D. K. and Mays, L.W., (2004). *Groundwater Hydrology (Third Edition)*. New Jersey: Wiley.

[2] [2Tuấn, L. A., (2019). Quản lý tài nguyên nước bền vững, ứng phó với biến đổi khí hậu ở Đồng bằng sông Cữu Long [Sustainable Water Resource Management and Climate Change Adaptation in the Mekong Delta]. *Tạp Chí Khoa Học Và Công Nghệ Việt Nam*, Vol. 7, 13-15.

[3] Xu, T., Valocchi, A. J., Choi, J. and Amir, E., (2014). Use of Machine Learning Methods to Reduce Predictive Error of Groundwater Models. *Groundwater*, Vol. 52(3), 448-460. https://doi.org/10.1111/gwat.12112.

[4] Sahoo, S., Russo, T. A., Elliott, J. and Fosster, I., (2017). Machine Learning Algorithms for Modeling Groundwater Level Changes in Agricultural Regions of the US. *Water Resources Research*, Vol. 53(5), 3878-3895. https://doi.org/10.1002/2016WR019933.

[5] Knoll, L., Breuer, L. and Bach, M., (2019). Large Scale Prediction of Groundwater Nitrate Concentrations from Spatial Data Using Machine Learning. *Science of the Total Environment*, Vol. 668, 1317-1327. https://doi.org/10.1016/j.scitotenv.2019.03.015.

[6] Hussein, E. A., Thron, C., Ghaziasgar, M., Bagula, A. and Vaccari, M., (2020). Groundwater Prediction Using Machine-Learning Tools. *Algorithms*, Vol. 13(11). https://doi.org/10.3390/a13110300.

[7] El Bilali, A., Taleb, A. and Brouziyne, Y., (2021). Groundwater Quality Forecasting Using Machine Learning Algorithms for Irrigation Purposes. *Agricultural Water Management*, Vol. 245. https://doi.org/10.1016/j.agwat.2021.106625

[8] Majumdar, S., Smith, R., J. J. Butler, Jr. and Lakshmi, V., (2020). Groundwater Withdrawal Prediction Using Integrated Multitemporal Remote Sensing Data Sets and Machine Learning. *Water Resources Research*, Vol. 56(11). https://doi.org/10.1029/2020WR028059.

[9] Mosavi, A., Hosseini, F. S., Choubin, B., Abdolshahnejad, M., Gharechaee, H., Lahijanzadeh, A. and Dineva, A. A., (2020). Susceptibility Prediction of Groundwater Hardness Using Ensemble Machine Learning Models. *Water*, Vol. 12(10). https://doi.org/10.3390/w12102770.

[10] Rohde, M.M., Biswas, T., Housman, I. W., Campbell, L. S., Klausmeyer, K. R. and Howard, J. K., (2021). A Machine Learning Approach to Predict Groundwater Levels in California Reveals Ecosystems at Risk. *Frontiers in Earth Science*, Vol. 9. https://doi.org/10.3389/feart.2021.784499.

[11] Pragnaditya, M., Abhijit, M., Bhanja, S. N., Kumar, R. R., Sudeshna, S. and Anwar, Z., (2021). Machine-Learning-Based Regional-Scale Groundwater Level Prediction Using GRACE. *Hydrogeology Journal*, Vol. 29(3), 1027-1042.

[12] Namous, M., Hssaisoune, M., Pradhan, B., Lee, C. K., Alamri, A., Elaloui, A., Edahbi, M., Krimissa, S., Eloudi, H., Ouayah, M., Elhimer, H. and Tagma, T., (2021). Spatial Prediction of Groundwater Potentiality in Large Semi-Arid and Karstic Mountainous Region Using

Machine Learning Models. *Water*, Vol. 13(16). https://doi.org/10.3390/w13162273.

[13] Afrifa, S., Zhang, T., Appiahene, P. and Varadarajan, V., (2022). Mathematical and Machine Learning Models for Groundwater Level Changes: A Systematic Review and Bibliographic Analysis. *Future Internet*, Vol. 14(9). https://doi.org/10.3390/fi14090259.

[14] Haggerty, R., Sun, J., Yu, H. and Li, Y., (2023). Application of Machine Learning in Groundwater Quality Modeling: A Comprehensive Review. *Water Research*, Vol. 233. https://doi.org/10.1016/j.watres.2023.119745.

[15] Singha, S., Pasupuleti, S., Singha, S. S., Singh, R. and Kumar, S., (2021). Prediction of Groundwater Quality Using Efficient Machine Learning Technique. *Chemosphere*, Vol. 276. https://doi.org/10.1016/j.chemosphere.2021.130265.

[16] Pham, Q. B., Kumar, M., Nunno, F. D., Elbeltagi, A., Granata, F., Reza Md., A., Islam, T., Talukdar, S., Cuong, N. X., Ahmed, A. N. and Duong, T. A., (2022). Groundwater Level Prediction Using Machine Learning Algorithms in a Drought-Prone Area. *Neural Computing Applications*, Vol. 34(13), 10751-10773. https://doi.org/10.1007/s00521-022-06971-9.

[17] Osman, A. I. A., Ahmed, A. N., Huang, Y. F., Kumar, P., Birima, A. H., Sherrif, M., Sefelnasr, A., Ebraheemand, A. A. and El-Shafie, A., (2022). Past, Present, and Perspective Methodology for Groundwater Modeling-Based Machine Learning Approaches. *Archives of Computational Methods in Engineering*, Vol. 29(6), 3843-3859. https://doi.org/10.1007/s11831-021-09659-5.

[18] Sapitang, M., Ridwan, W. M., Ahmed, A. N., Fai, C. M. and El-Shafie, A., (2021). Groundwater Level as an Input to Monthly Predicting of Water Level Using Various Machine Learning Algorithms. *Earth Science Informatics*, Vol. 14(3), 1269-1283. https://doi.org/10.1007/s12145-021-00615-7.

[19] Singh, A., Patel, S., Bhadani, V., Kumar, V. and Gaurav, K., (2024). AutoML-GWL: Automated Machine Learning Model for the Prediction of Groundwater Level. *Engineering Applications of Artificial Intelligence*, Vol. 127. https://doi.org/10.1016/j.engappai.2023.107405.

[20] Barzegar, R., Moghaddam, A. A., Adamowski, J. and Fijani, E., (2017). Comparison of Machine Learning Models for Predicting Fluoride Contamination in Groundwater. *Environmental Earth Sciences*, Vol. 31, 2705-2718. https://doi.org/10.1007/s12665-017-6896-9.

[21] Cường, L. P. and Thắng, N. V., (2022). Ứng Dụng Mô Hình Học Máy Dự Báo Chất Lượng Nước Dưới Đất: Điển Hình Tại Khu Vực Thành Phố Hội An, Tỉnh Quảng Nam [Application of Machine Learning Models for Predicting Groundwater Quality: A Case Study in Hoi An City, Quang Nam Province]. *Tạp Chí Khoa Học Và Công Nghệ - Đại Học Đà Nẵng*, Vol. 2022, 106-110.

[22] Kim, K. G., (2016). Book Review: Deep Learning. *Healthcare Informatics Research*, Vol. 22(4), 351-354. https://doi.org/10.4258/hir.2016.22.4.351.

[23] Trong, N. G., Le, H. A., Cuong, N. V., Quang, P. N., Long, N. H. and Dieu, T. B., (2023). Spatial Prediction of Fluvial Flood in High-Frequency Tropical Cyclone Area Using TensorFlow 1D-Convolution Neural Networks and Geospatial Data. *Remote Sensing*, Vol. 15(22). https://doi.org/10.3390/rs15225429.

[24] Tinh, L. D., Thao, D. T. P., Thang, T. D., Hop, D. T. and Trong, N. G., (2025). Evaluating the Performance of CNN (Conv1D) and CNN (Conv3D) Models in GNSS Data Analysis. *Journal of Hydrometeorology*, 771, 55-64. https://doi.org/10.36335/VNJHM.2025(771).

[25] Goodfellow, I., Bengio, Y. and Courville, A., (2016). *Deep Learning*. Cambridge: MIT Press.

[26] Dutta, K. K., (2019). Multi-Class Time Series Classification of EEG Signals with Recurrent Neural Networks. *2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*. 1-6. https://doi.org/10.1109/CONFLUENCE.2019.8776965.

[27] Trong, N. G. and Quy, B. N., (2024). Analyzing Tidal Data Sequences Using Gated Recurrent Unit (GRU). *Journal of Hydrometeorology*, 39-46. https://doi.org/10.36335/VNJHM.2024(765).

[28] Kurumatani, K., (2020). Time Series Forecasting of Agricultural Product Prices Based on Recurrent Neural Networks and its Evaluation Method. *SN Applied Sciences*, Vol. 2(8). https://doi.org/10.1007/s42452-020-03225-9.

[29] Chollet, F., (2021). *Deep Learning with Python*. New York: Simon & Schuster.

[30] VanderPlas, J., (2023). *Python Data Science Handbook: Essential Tools for Working with Data* (Second Edition). Sebastopol, CA: O'Reilly Media.