International Journal of Scientific Research and Engineering Development-– Volume 9 Issue 6, Nov – Dec 2026
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Deep Learning-Based Groundwater Level Prediction Using Multivariate Time-Series Analysis and Spatial Visualization

Jahanara Shaik*, Srujan Amaragatti*, Indrajith A S*, Tejjas A R*, Sanketh Kulkarni*
*(Department of Information Science and Engineering, CMR Institute of Technology, Bengaluru, Karnataka, India)
Email: jahanarashaik@gmail.com, srujan.ise24le@cmrit.ac.in, iindrajithas@gmail.com, eshwartejjas@gmail.com, sankethkulkarni56@gmail.com

----------**********----------

Abstract:

Groundwater-level forecasting is an important component of water-resource monitoring because groundwater conditions vary with environmental drivers and local hydrogeological characteristics. This paper presents a groundwater prediction and visualization system that combines historical groundwater observations from the Central Ground Water Board (CGWB), India, with meteorological variables retrieved from NASA's Prediction of Worldwide Energy Resources (POWER) service. Five consecutive annual observations of groundwater level, rainfall, temperature, and humidity-related data are used to predict the groundwater level for the following year. The system compares Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Hybrid Spatio-Temporal GRU models. In the reported model comparison, GRU obtains an RMSE of 2.1616 m below ground level (mbgl), an MAE of 1.2821 mbgl, and an R^2 of 0.9242. The hybrid model, which combines a temporal branch with station latitude and longitude, obtains an RMSE of 2.1885 mbgl, an MAE of 1.3178 mbgl, and an R^2 of 0.9223. An interactive Leaflet-based map links predictions with station metadata. The results indicate that the GRU model provides the strongest aggregate performance among the evaluated deep-learning models under the reported test protocol.

Keywords — **groundwater prediction, time-series forecasting, LSTM, GRU, spatio-temporal learning, NASA POWER, CGWB, spatial visualization.**

----------**********----------

I. INTRODUCTION

Groundwater supports agricultural, domestic, and industrial water requirements. Its observed level is affected by recharge, extraction, precipitation, hydrogeological conditions, and other local factors. Forecasting groundwater levels is challenging because these influences interact over time and may produce nonlinear temporal patterns. Central Ground Water Board monitoring provides observations of groundwater depth at stations across India, while meteorological products can provide contextual environmental variables for modelling [1], [2].

Recurrent neural networks are used in sequential prediction because they can learn relationships among ordered observations. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks use gating mechanisms to regulate information retained from earlier time steps. Prior groundwater studies have investigated GRU-based forecasting, time-delayed machine-learning models, CNN–LSTM combinations, and decomposition-assisted LSTM approaches [3]–[5].

This work updates an earlier regional groundwater-prediction prototype into a system that evaluates multiple deep-learning architectures and connects their outputs to a geographical interface. The evaluated task is one-year-ahead prediction from five consecutive annual observations. The paper compares LSTM, GRU, and a Hybrid Spatio-Temporal GRU model and describes an application for station selection and map-based exploration. A separate Random Forest model is retained as a

 ©IJSRED: All Rights are Reserved

regional Phase 1 baseline; because its modelling setup differs from the Phase 2 sequence models, its metrics are reported separately from the principal deep-learning comparison.

The main contributions are: (1) a multi-state five-year multivariate pipeline for one-year-ahead prediction; (2) controlled LSTM, GRU, and coordinate-aware Hybrid GRU comparison; (3) evaluation of hybrid architecture and residual-fusion candidates; and (4) analysis showing that added complexity did not consistently improve held-out performance. Predictions are also linked to station metadata through a geographical interface.

II. RELATED WORK

Recent groundwater-level forecasting research shows a broad shift from single-model recurrent networks toward hybrid, attention-based, decomposition-assisted, transformer, and spatially aware architectures. Gharehbaghi et al. evaluated meteorologically sensitive GRU structures for monthly groundwater prediction in the Urmia Plain, while Yang and Zhang proposed a CNN–LSTM model with meta-learning for the Heihe River region. Nazari et al. later showed that EMD–LSTM can improve forecasts when groundwater series contain strong trend-driven non-stationarity. Deep recurrent models have also been evaluated for cross-well prediction and uncertainty assessment by Eghrari et al. [3]–[6].

Recent studies increasingly incorporate spatial, meteorological, and multi-source information through attention-GRU, TCN/LSTM, ConvAE-LSTM, wavelet, geostatistical, and remote-sensing approaches [7]–[13].

Recent work further addresses data quality, attention, Transformers, uncertainty, and spatial generalization using interpolation-assisted deep learning, MODWPT–LSTM, TCN–LSTM–Attention, Bayesian imputation, Temporal Fusion Transformers, multi-site LSTM, adjacent-well information, graph–recurrent models, and Bayesian TimesNet with SHAP interpretation [14]–[24]. Tables I and II summarize these studies.

The survey identifies four recurring limitations: localized study areas, short forecast horizons, spatial models requiring richer hydrogeological or adjacent-well information, and limited evaluation of forecasting together with station-level visualization. This study addresses these gaps through a common five-year annual formulation across a multi-state Indian dataset, controlled LSTM/GRU/hybrid comparison, and station-linked geographical visualization.

A. Research Gap

The literature indicates that high-performing groundwater models are often demonstrated in localized basins, individual wells, or short forecast horizons. Recent studies increasingly incorporate spatial information through adjacent-well graphs, hydrogeological units, remote sensing, or learned site embeddings, but these approaches generally require richer spatial relationships or additional data structures. At the same time, review evidence points to a gap between academic model development and practical deployment at scale.

For the present study, the specific gap is the lack of a simple, controlled multi-state evaluation that uses the same five-year annual multivariate sequence formulation to compare a temporal LSTM, a parameter-efficient GRU, and a coordinate-aware spatio-temporal GRU while retaining station-level visualization. The proposed system addresses this gap by using CGWB observations with NASA POWER meteorological variables, maintaining a chronological held-out test protocol, explicitly testing whether latitude and longitude improve the common GRU baseline, and exposing the predictions through a geographical interface. Importantly, the experiments also test whether additional hybrid complexity produces a consistent held-out improvement; the results show that it does not under the evaluated protocol. This negative finding is treated as part of the research contribution rather than being omitted.

 ©IJSRED: All Rights are Reserved

TABLE I
SYSTEMATIC LITERATURE SURVEY OF RECENT GROUNDWATER-LEVEL FORECASTING STUDIES (PART I)

Study	Method	Dataset / Setting	Metrics	Key Finding	Limitation / Remaining Gap
Gharehbaghi et al. (2022) [3]	GRU seq2seq variants	42 piezometers, Urmia Plain; monthly 2002–2017	RMSE, R^2, grade	Double-GRU variant achieved strong regional prediction (R^2 about 0.91).	Regional mean monthly setting; limited spatial transfer evidence.
Yang and Zhang (2022) [4]	CNN–LSTM + meta-learning	Middle/lower Heihe River, China; groundwater + meteorological inputs	Prediction error metrics	Hybrid CNN–LSTM improved robustness under limited samples.	Basin-specific; does not test a multi-state annual formulation.
Nazari et al. (2025) [5]	EMD-/WT-LSTM	Three wells, San Bernardino County; 2017–2022	RMSE	EMD–LSTM reduced errors substantially for trend-driven non-stationarity.	Benefits were not consistent for randomly fluctuating wells.
Eghrari et al. (2023) [6]	LSTM and GRU + repeated runs	One well used for training; six other wells for prediction	MAE, RMSE, NRMSE, R^2	LSTM slightly outperformed GRU and repeated runs supported uncertainty assessment.	Training was centered on one well; transfer setting is localized.
May-Lagunes et al. (2023) [7]	ML, ensembles, deep learning, Transformer tests	Sacramento River Basin, California; 3-month horizon	RMSE, MSPE	XGBoost gave best reported 3-month result; hydrometeorological variables improved forecasting.	Short forecast horizon and regional study area.
Tian et al. (2023) [8]	Attention-GRU	North China Plain; ecological water-supplement context	RMSE, R^2	Attention-GRU outperformed RNN and LSTM in the reported setting.	Strongly tied to a specific water-supplement context.
Zhang et al. (2023) [9]	TCN and LSTM	Two coastal wells; hourly data; 1–15 day leads	RMSE, R^2	TCN slightly outperformed LSTM, with accuracy decreasing as lead time increased.	Only two wells and short lead horizons.
Kow et al. (2024) [10]	ConvAE–LSTM	Jhuoshuei watershed; spatial images + temporal series	R^2, forecast error	ConvAE–LSTM improved regional multi-horizon forecasting and extracted spatial information.	More complex spatial data representation than simple station metadata.
Zhang et al. (2023) [11]	WT-LSTM, WT-RF, WT-XGB + SHAP	Remote-sensing-assisted groundwater forecasting	Error metrics, SHAP	WT-LSTM was strongest among tested hybrids; SHAP improved interpretation.	Requires multiple remote-sensing products and wavelet processing.
Collados-Lara et al. (2023) [12]	NAR/NARX/Elman + geostatistics	51 wells, Campo de Montiel, Spain	RMSE; uncertainty series	Integrated climatic/geostatistical framework achieved useful short-term forecasts.	Accuracy varied by well and horizon; short-term focus.
Bouramtane et al. (2023) [13]	LSTM + XGBoost feature selection	Five wells, Oum Er-Rbia Basin, Morocco; remote sensing inputs	RMSE, MAE, R^2	Selected remote-sensing inputs improved LSTM performance across wells.	Five-well basin study; dependence on remote-sensing features.

TABLE II
SYSTEMATIC LITERATURE SURVEY OF RECENT GROUNDWATER-LEVEL FORECASTING STUDIES (PART II)

Study	Method	Dataset / Setting	Metrics	Key Finding	Limitation / Remaining Gap
Abdi et al. (2024) [14]	Interpolation + DNN/CNN	34 wells, Azarshahr Plain; incomplete records	RMSE	M5P interpolation improved data quality; CNN outperformed DNN.	Interpolation quality becomes important when records are sparse or missing.
Roy et al. (2024) [15]	MODWPT + LSTM + RF feature selection	Bangladesh monitoring wells; up to 3-week horizons	RMSE, SI, MAE-related indices	LSTM-MODWPT improved forecasts over standalone LSTM.	Short horizon and decomposition-specific pipeline.
Chen et al. (2024) [16]	TCN–LSTM–Attention	Two wells in an earthquake-precursor case study	Forecasting/error metrics	Hybrid temporal-attention architecture supports groundwater prediction and anomaly analysis.	Very localized two-well application with a seismic focus.

 ©IJSRED: All Rights are Reserved

Study	Method	Dataset / Setting	Metrics	Key Finding	Limitation / Remaining Gap
Chen et al. (2024) [17]	Bayesian imputation + LSTM/CNN	Middle Creek, New South Wales; multiple boreholes	RMSE, NSE	Regional multivariate LSTM using rainfall performed strongly after missing-data treatment.	Performance depends on well density and imputation quality.
Sun et al. (2024) [18]	Transformer vs. CNN/LSTM	Zhuoshui River Basin, Taiwan	Forecasting error, trend/peak accuracy	Transformer improved groundwater prediction and captured peaks/trends.	Requires larger sequence-model capacity; spatial transfer not the main focus.
Ali et al. (2024) [19]	Temporal Fusion Transformer + LSTM variants	Thames Basin; daily 2001–2023	RMSE, R^2; walk-forward/holdout	TFT outperformed tested LSTM variants across aquifer types and horizons up to 60 days.	Daily short-to-medium horizons; study focused on three aquifers.
Ali et al. (2024) review [20]	Review of DL groundwater studies	47 GWL modelling papers within 91 ML groundwater studies	Review synthesis	Identified dominance of monthly/daily studies and limited practical industrial deployment.	Review itself identifies the need for broader operational evaluation.
Nolte et al. (2025) [21]	Multi-site LSTM with trainable site embeddings	>1,800 wells across nine global regions	NSE and cross-site robustness	Site embeddings supported scalable multi-site prediction under data scarcity.	Static descriptors and site-specific generalization remain challenging.
Han et al. (2025) [22]	LSTM, CNN–LSTM, CNN–LSTM–Attention using adjacent wells	Spatially separated wells; distance analysis	NSE	Spatial information from adjacent wells can help, with attention improving use of nearby-well information.	Performance depends on distance and availability of neighboring wells.
Zhuang et al. (2025) [23]	GraphSAGE + multi-branch GRU + cross-attention	Jinan City monitoring wells	MAE, RMSE, R^2	STGPM achieved strong test performance and explicitly evaluated wells not used in training.	More complex graph/hydro-connectivity requirements than coordinate-only models.
Peng et al. (2025) [24]	Bayesian TimesNet + SHAP	19 wells across three U.S. hydroclimatic regions; monthly multi-step	NSE, RMSE, uncertainty	Improved accuracy, probabilistic uncertainty quantification, and explainability.	Small number of wells; advanced probabilistic architecture increases complexity.

III. DATASET AND PREPROCESSING

A. Data Sources

Groundwater-level observations were obtained from the Central Ground Water Board (CGWB), India. CGWB describes a nationwide groundwater monitoring network and makes water-level information available through government water-information platforms [1]. Meteorological variables were retrieved from NASA's Prediction of Worldwide Energy Resources (POWER) service, which provides globally available meteorological and solar data products through data access tools and APIs [2]. The project identifies rainfall, temperature, and humidity-related variables as meteorological inputs.

The final evaluation report describes 385,386 multi-state groundwater observations spanning 1994–2024 and covering 38 States/Union Territories. The temporal models use groundwater level (WL, mbgl), rainfall (mm), temperature (°C), and relative humidity (%); the hybrid model also receives latitude and longitude. The reported NASA POWER parameter codes are T2M (temperature at 2 m), RH2M (relative humidity at 2 m), and PRECTOTCORR (corrected precipitation total). The available report does not unambiguously document the final temporal aggregation and station-level extraction procedure used to align these meteorological variables with annual groundwater records. Those preprocessing details must be checked against the data-generation code before submission, because aggregation choices affect the meaning of the model inputs.

B. Sequence Construction

Observations are grouped by monitoring location and arranged chronologically. For each eligible location, five consecutive annual observations are used as input and the groundwater level in the subsequent year is the target. Sequences with missing years that prevent a valid consecutive input-to-target interval are excluded. This setup represents one-year-ahead forecasting from a five-year history; it does not by itself establish recursive multi-year forecasting performance.

Feature scaling is applied using parameters fitted on the training data and then applied to validation

 ©IJSRED: All Rights are Reserved

and test data. The definitive Phase 2 evaluation uses a chronological split with training targets through 2018, validation targets in 2019–2021, and a strictly held-out test set for 2022–2023. Sequences targeting 2024 are excluded from the reported test evaluation. The scalers are fitted on the training partition only and then applied to validation and test data.

IV. METHODOLOGY

Fig. 1 summarizes the complete proposed workflow. The workflow is divided into six modules: (1) groundwater and meteorological data acquisition, (2) cleaning and annual alignment, (3) five-year sequence construction and training-only scaling, (4) parallel temporal and spatial-temporal model branches, (5) chronological validation and held-out testing, and (6) station-level inference and map visualization.

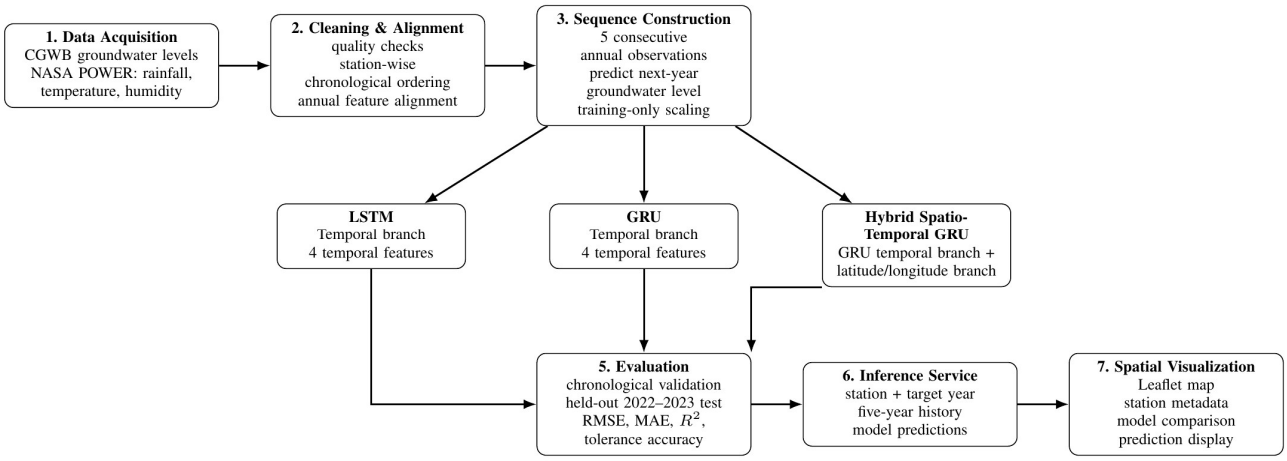


Fig. 1 Proposed methodology workflow for multi-state groundwater-level prediction, model evaluation, and station-level spatial visualization.

A. Workflow Modules

Data acquisition and alignment collect groundwater observations from CGWB and meteorological variables from NASA POWER and associate them with monitoring locations and years. Sequence construction then converts the station-wise records into supervised samples using five consecutive annual observations to predict the following year. The temporal branch feeds groundwater level, rainfall, temperature, and humidity-related variables to LSTM or GRU, whereas the hybrid model additionally encodes latitude and longitude. The resulting models are compared under the same chronological evaluation protocol. Finally, the inference service accepts a selected station and target year and the application presents predictions with station metadata on a Leaflet map.

B. LSTM Baseline

The LSTM model processes the five-step multivariate sequence to learn temporal dependencies in historical groundwater and meteorological variables. Its gated memory cells regulate information flow across time steps. The learned temporal representation is passed to a regression output to estimate the target-year groundwater level.

C. GRU Baseline

The GRU model provides a recurrent baseline using update and reset gates to control how information is retained and updated across the sequence. It is trained for the same general input-to-target forecasting task as LSTM, allowing the two architectures to be compared under the reported evaluation protocol.

D. Hybrid Spatio-Temporal GRU

The hybrid model contains two branches. The temporal branch processes the five-step sequence of groundwater level, rainfall, temperature, and humidity-related variables through a GRU. A separate dense branch encodes the station's latitude and longitude. The temporal and spatial

 ©IJSRED: All Rights are Reserved

representations are concatenated and passed through dense layers to estimate the next-year groundwater level. This design enables the prediction to condition on both historical observations and station coordinates.

E. Regional Random Forest Baseline

Phase 1 of the project uses a Random Forest model for a regional Andhra Pradesh baseline. It is based on a separate tabular setup and is not treated as a strictly controlled architecture-only comparison with the Phase 2 deep-learning models. Its metrics are therefore presented as a project-level reference, with the difference in experimental setup acknowledged.

F. Evaluation Metrics

The models are evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2):

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

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (3)$$

Here, y_i is the observed groundwater level, $\hat{y}_i$ is the predicted value, $\bar{y}$ is the mean observed target, and n is the number of test samples. Lower RMSE and MAE indicate smaller errors, while higher R^2 indicates greater explained variance relative to the mean-prediction reference.

V. RESULTS AND DISCUSSION

Table III presents the reported test metrics for the three Phase 2 deep-learning models. The combined model comparison in Fig. 2 summarizes validation loss and test-set performance. The output comparison in Fig. 3 shows the observed and predicted groundwater levels for all three models on the held-out 2022–2023 test set.

TABLE III
REPORTED TEST-SET PERFORMANCE OF DEEP-LEARNING MODELS

Model	RMSE (mbgl)	MAE (mbgl)	R^2
LSTM	2.2219	1.3368	0.9200
GRU	**2.1616**	**1.2821**	**0.9242**
Hybrid Spatio-Temporal GRU	2.1885	1.3178	0.9223

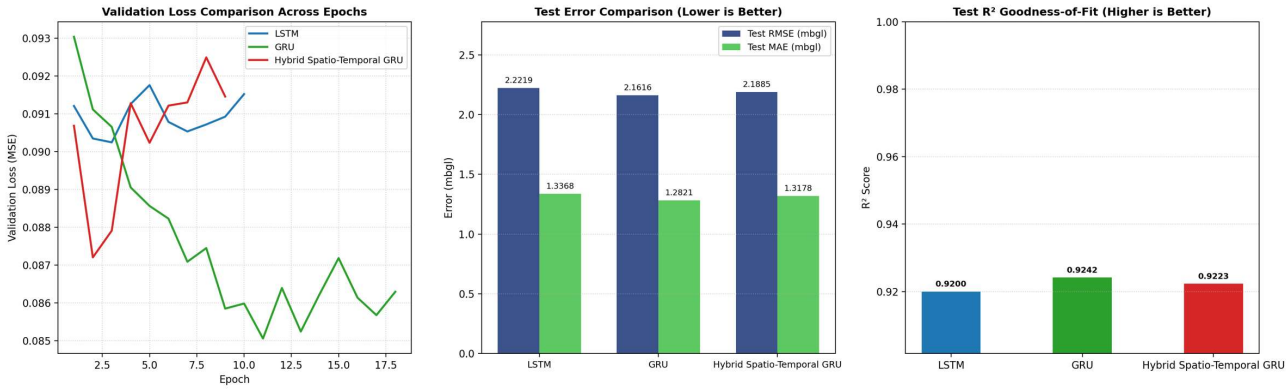


Fig. 2 Comparison of validation loss, test RMSE/MAE, and test R^2 for the LSTM, GRU, and Hybrid Spatio-Temporal GRU models.

 ©IJSRED: All Rights are Reserved

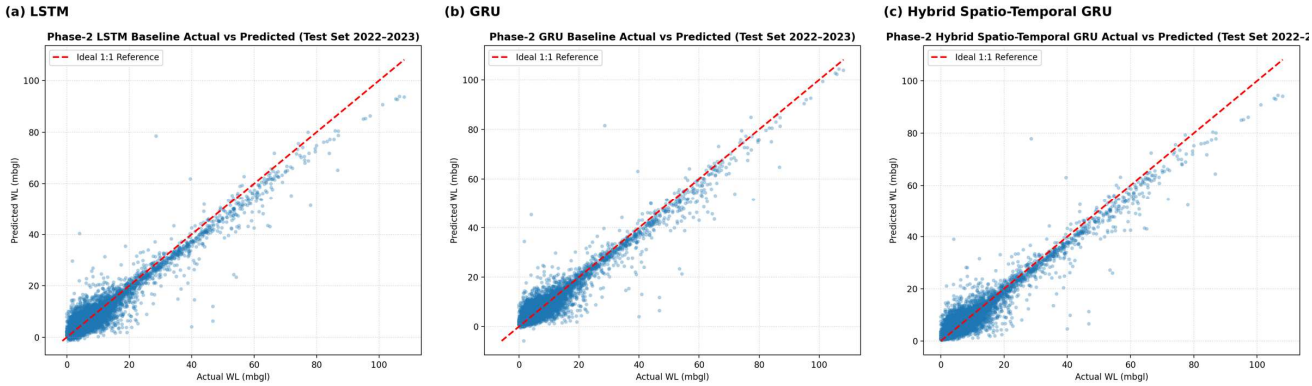


Fig. 3 Actual-versus-predicted groundwater level outputs for the LSTM, GRU, and Hybrid Spatio-Temporal GRU models on the held-out 2022–2023 test set. The dashed line denotes the ideal 1:1 relationship.

GRU achieved the best aggregate performance, with RMSE 2.1616 mbgl, MAE 1.2821 mbgl, and R^2 0.9242. LSTM and Hybrid GRU obtained RMSE values of 2.2219 and 2.1885 mbgl, respectively. The hybrid model did not improve aggregate accuracy over GRU: its RMSE was 0.0269 mbgl higher and its R^2 was 0.0019 lower. Thus, GRU is numerically strongest, while the hybrid provides coordinate-aware modelling without demonstrated unseen-well superiority.

A. Training and Validation Behaviour

The best validation epochs were 3, 11, and 2 for LSTM, GRU, and Hybrid GRU, with scaled validation losses of 0.0902, 0.0851, and 0.0872, respectively. The fluctuating curves support checkpoint selection based on validation performance rather than training loss alone; scaled validation loss is not directly comparable with test RMSE or MAE in mbgl.

B. Additional Hybrid Architecture and Training Experiments

Four hybrid variants were evaluated: baseline V0, wider spatial/fusion V1, adaptive-learning-rate V2, and stacked-GRU V3. Table IV shows that V0 achieved the best RMSE (2.1666 mbgl), MAE (1.2937 mbgl), and R^2 (0.9239); added architectural or training complexity did not improve held-out performance.

TABLE IV
SEPARATE HYBRID VARIANT EXPERIMENT (RUN 2)

Variant	Params.	RMSE	MAE	R^2
V0: Hybrid baseline	**14,809**	**2.1666**	**1.2937**	**0.9239**
V1: Wider spatial/fusion	17,201	2.2434	1.3928	0.9184
V2: Adaptive learning rate	17,201	2.2666	1.4267	0.9167
V3: Stacked GRU	25,585	2.2273	1.3530	0.9196

The one-shot residual-fusion experiment likewise did not establish improvement (RMSE 2.2141 vs. 2.1975 mbgl; R^2 0.9205 vs. 0.9217).

VI. LIMITATIONS

The study does not explicitly model pumping, aquifer properties, geology, land use, or local water-management practices. Unseen-well generalization and multi-year forecasting require separate evaluation, and complete dataset/aggregation documentation should be validated independently.

VII. CONCLUSION

The study uses a controlled multi-state comparison to test whether spatial coordinates and added hybrid complexity improve held-out forecasting under a common protocol.

This paper presents a groundwater-level prediction system combining multivariate sequence learning with geographical visualization. LSTM, GRU, and Hybrid Spatio-Temporal GRU were evaluated for one-year-ahead prediction from five annual observations. GRU achieved the strongest

 ©IJSRED: All Rights are Reserved

aggregate metrics, while the coordinate-aware hybrid model was slightly weaker.

Future work should test unseen-well and regional generalization, additional hydrogeological variables, and multi-year forecasting.

REFERENCES

[1] Central Ground Water Board, Government of India, "Ground water level monitoring." [Online]. Available: https://cgwb.gov.in/ground-water-level-monitoring. Accessed: Oct. 3, 2026.

[2] NASA Langley Research Center, "NASA Prediction of Worldwide Energy Resources (POWER): API and data access documentation." [Online]. Available: https://power.larc.nasa.gov/. Accessed: Oct. 3, 2026.

[3] A. Gharehbaghi, R. Ghasemlounia, F. Ahmadi, and M. Albaji, "Groundwater level prediction with meteorologically sensitive Gated Recurrent Unit (GRU) neural networks," *Journal of Hydrology*, vol. 612, Art. no. 128262, 2022, doi: 10.1016/j.jhydrol.2022.128262.

[4] X. Yang and Z. Zhang, "A CNN-LSTM model based on a meta-learning algorithm to predict groundwater level in the middle and lower reaches of the Heihe River, China," *Water*, vol. 14, no. 15, Art. no. 2377, 2022, doi: 10.3390/w14152377.

[5] A. Nazari, M. Jamshidi, A. Roozbahani, and B. Golparvar, "Groundwater level forecasting using empirical mode decomposition and wavelet-based long short-term memory (LSTM) neural networks," *Groundwater for Sustainable Development*, vol. 28, Art. no. 101397, 2025, doi: 10.1016/j.gsd.2024.101397.

[6] Z. Eghrari, M. R. Delavar, M. Zare, M. Mousavi, B. Nazari, and S. Ghaffarian, "Groundwater level prediction using deep recurrent neural networks and uncertainty assessment," *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. X-1/W1-2023, pp. 493–500, 2023, doi: 10.5194/isprs-annals-X-1-W1-2023-493-2023.

[7] G. May-Lagunes, V. Chau, E. Ellestad, L. Greengard, P. D'Odorico, P. Vahabi, A. Todeschini, and M. Girotto, "Forecasting groundwater levels using machine learning methods: The case of California's Central Valley," *Journal of Hydrology X*, vol. 21, Art. no. 100161, 2023, doi: 10.1016/j.hydroa.2023.100161.

[8] T. Nan, W. Cao, Z. Wang, Y. Gao, L. Zhao, X. Sun, and J. Na, "Evaluation of shallow groundwater dynamics after water supplement in North China Plain based on attention-GRU model," *Journal of Hydrology*, vol. 625, Art. no. 130085, 2023, doi: 10.1016/j.jhydrol.2023.130085.

[9] X. Zhang, F. Dong, G. Chen, and Z. Dai, "Advance prediction of coastal groundwater levels with temporal convolutional and long short-term memory networks," *Hydrology and Earth System Sciences*, vol. 27, pp. 83–96, 2023, doi: 10.5194/hess-27-83-2023.

[10] P.-Y. Kow, J.-Y. Liou, W. Sun, L.-C. Chang, and F.-J. Chang, "Watershed groundwater level multistep ahead forecasts by fusing convolutional-based autoencoder and LSTM models," *Journal of Environmental Management*, vol. 351, Art. no. 119789, 2024, doi: 10.1016/j.jenvman.2023.119789.

[11] Q. Zhang, P. Li, X. Ren, J. Ning, J. Li, C. Liu, Y. Wang, and G. Wang, "A new real-time groundwater level forecasting strategy: Coupling hybrid data-driven models with remote sensing data," *Journal of Hydrology*, vol. 625, Art. no. 129962, 2023, doi: 10.1016/j.jhydrol.2023.129962.

[12] A. J. Collados-Lara, D. Pulido-Velazquez, L. G. B. Ruiz, M. C. Pegalajar, E. Pardo-Igúzquiza, and L. Baena-Ruiz, "A parsimonious methodological framework for short-term forecasting of groundwater levels," *Science of the Total Environment*, vol. 881, Art. no. 163328, 2023, doi: 10.1016/j.scitotenv.2023.163328.

[13] T. Bouramtane, M. Leblanc, I. Kacimi, H. Ouatiki, and A. Boudhar, "The contribution of remote sensing and input feature selection for groundwater level prediction using LSTM neural networks in the Oum Er-Rbia Basin, Morocco," *Frontiers in Water*, vol. 5, 1241451, 2023, doi: 10.3389/frwa.2023.1241451.

[14] E. Abdi, M. Ali, C. A. G. Santos, A. Olusola, and M. A. Ghorbani, "Enhancing groundwater level prediction accuracy using interpolation techniques in deep learning models," *Groundwater for Sustainable Development*, vol. 26, Art. no. 101213, 2024.

[15] D. K. Roy, A. A. Hashem, M. L. Reba, D. L. Leslie, and J. Nowlin, "A maximal overlap discrete wavelet packet transform coupled with an LSTM deep learning model for improving multilevel groundwater level forecasts," *Discover Water*, vol. 4, Art. no. 16, 2024, doi: 10.1007/s43832-024-00073-1.

[16] X. Chen, L. Yang, X. Liao, H. Zhao, and S. Wang, "Groundwater level prediction and earthquake precursor anomaly analysis based on TCN-LSTM-Attention network," *IEEE Access*, vol. 12, pp. 176696–176718, 2024, doi: 10.1109/ACCESS.2024.3505942.

[17] E. Chen, M. S. Andersen, and R. Chandra, "Deep learning framework with Bayesian data imputation for modelling and forecasting groundwater levels," *Environmental Modelling & Software*, vol. 178, Art. no. 106072, 2024, doi: 10.1016/j.envsoft.2024.106072.

[18] W. Sun, L.-C. Chang, and F.-J. Chang, "Deep dive into predictive excellence: Transformer's impact on groundwater level prediction," *Journal of Hydrology*, vol. 636, Art. no. 131250, 2024, doi: 10.1016/j.jhydrol.2024.131250.

[19] A. J. Ali, A. A. Ahmed, and M. F. Abbod, "Groundwater level predictions in the Thames Basin, London over extended horizons using Transformers and advanced machine learning models," *Journal of Cleaner Production*, vol. 484, Art. no. 144300, 2024, doi: 10.1016/j.jclepro.2024.144300.

[20] A. S. A. Ali, F. Jazaei, P. Babakhani, M. M. Ashiq, A. Bakhshaee, B. Waldron, and A. A. Ali, "An overview of deep learning applications in groundwater level modeling: Bridging the gap between academic research and industry applications," *Applied Computational Intelligence and Soft Computing*, 2024, Art. no. 9480522, doi: 10.1155/2024/9480522.

[21] A. Nolte, B. Heudorfer, S. Bender, and J. Hartmann, "Multi-site deep learning for groundwater level prediction across global datasets: Toward scalable applications under data scarcity," *Journal of Hydroinformatics*, vol. 27, no. 10, pp. 1632–1651, 2025, doi: 10.2166/hydro.2025.095.

[22] Z. Han, F. Li, Y. Zhao, and C. Liu, "Investigation into groundwater level prediction within a deep learning framework: Incorporating the spatial dynamics of adjacent wells," *Journal of Hydrology*, vol. 657, Art. no. 133097, 2025, doi: 10.1016/j.jhydrol.2025.133097.

[23] C. Zhuang, L. Cui, and Y. Cui, "Enhancing groundwater level prediction with a hybrid deep learning model in Jinan City, China," *Scientific Reports*, vol. 15, Art. no. 44535, 2025, doi: 10.1038/s41598-025-28200-5.

[24] Z. Peng, S. Mo, A. Y. Sun, J. Wu, X. Zeng, M. Lu, and X. Shi, "An explainable Bayesian TimesNet for probabilistic groundwater level prediction," *Water Resources Research*, vol. 61, Art. no. e2025WR040191, 2025, doi: 10.1029/2025WR040191.

 ©IJSRED: All Rights are Reserved