ISSN 2029-6991 / eISSN 2029-7009

VILNIUS TECH
Vilnius Gediminas Technical University

GEODESY and CARTOGRAPHY

2026
Volume 52
Issue 2
Pages 83–89
https://doi.org/10.3846/gac.2026.22179

UDC 528.8:556.16:004.93

A HYBRID DWTNN–MARS FRAMEWORK FOR MONTHLY LAKE WATER LEVEL FORECASTING IN THE LAKE VOLTA BASIN UNDER DATA-SCARCE CONDITIONS

Michael Stanley PEPRAH[1]✉, Edwin Kojo LARBI[2], Prince Opoku APPAU[3]

[1]IHTMOC Consulting Company Limited, Kumasi-Adiembra, Ghana
[2]Geo-Informatics Division, Building and Road Research Institute (CSIR-BRRI), Kumasi, Ghana
[3]Ghana National Gas Limited Company, 225 Osibisa Close, Airport West, Accra, Ghana

Article History:
- received 7 September 2024
- accepted 5 May 2026

Abstract. Accurate forecasting of Lake Water Level (LWL) fluctuations is essential for sustainable reservoir management, particularly in data-scarce tropical environments. This study develops and evaluates a hybrid Discrete Wavelet Transform Neural Network–Multivariate Adaptive Regression Splines (DWTNN–MARS) framework for monthly LWL prediction in the Lake Volta Basin, Ghana, using 28 years (1992–2020) of satellite altimetry data. The proposed approach integrates multi-resolution wavelet decomposition, nonlinear neural network pre-processing, and adaptive spline regression with generalized cross-validation-based pruning to effectively capture complex, non-stationary hydrological dynamics while controlling model complexity. A time-series-based validation strategy was adopted to prevent data leakage and ensure realistic predictive assessment. Model performance was evaluated using Prediction Correction Index (PCI), Arithmetic Mean Absolute Error (AMAE), Arithmetic Mean Square Error (AMSE), Arithmetic Mean Absolute Percentage Error (AMAPE), and Arithmetic Standard Deviation (ASD), and benchmarked against a DWTNN–ARIMA hybrid model. Results show that the DWTNN–MARS model achieved a PCI of 0.0215 m and ASD of 0.0003 m, indicating strong agreement between observed and predicted values, while the DWTNN–ARIMA model exhibited higher prediction bias (PCI = 0.2152 m) and greater residual dispersion (ASD = 0.0420 m). These findings demonstrate that the structured decomposition-regression architecture enhances predictive accuracy and improves the representation of seasonal variability and long-term storage dynamics. The study highlights the robustness and applicability of the proposed framework for large tropical reservoirs under limited hydro-meteorological data conditions and contributes to advancing data-driven hydrological forecasting methodologies.

Keywords: hydrological forecasting, wavelet transform, nonlinear modelling, reservoir dynamics, signal decomposition, model generalization.

✉Corresponding author. E-mail: ***mspeprah91@gmail.com***

1. Introduction

Lakes are among the most valuable freshwater resources on Earth, playing essential roles in hydropower generation, irrigation, fisheries, flood control, and ecological sustainability (Peprah & Larbi, 2021a). Lake Water Level (LWL) is a key physical indicator of lake system dynamics, and its fluctuations significantly influence hydrodynamic processes, water availability, and ecosystem stability (Zhu et al., 2020; Demir, 2021; Piasecki et al., 2017). Reliable forecasting of LWL is therefore critical for effective reservoir management, particularly in large artificial systems such as Lake Volta in Ghana.

Conventional approaches for LWL forecasting include statistical time-series models such as Autoregressive Integrated Moving Average (ARIMA), Kalman filtering, and classical regression techniques (Young et al., 2015; Kakahaji et al., 2013; Aksoy et al., 2013; Khatibi et al., 2014; Peprah & Larbi, 2021a), as well as physically based hydrodynamic models (Kebede et al., 2006; Huang et al., 2010). While physically based models offer detailed system representation, they require extensive hydro-meteorological datasets, including inflow, discharge, and meteorological variables, which are often unavailable or incomplete in many developing regions (Zhu et al., 2020). Statistical models, although less data-intensive, frequently struggle to capture the nonlinear and non-stationary characteristics inherent in hydrological time series.

In recent decades, Machine Learning (ML) techniques have gained considerable attention due to their ability to model complex nonlinear relationships without explicit physical assumptions (Demir, 2021; Mislan et al., 2018;

Peprah & Larbi, 2021b; Doğan et al., 2016). Methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and regression-based algorithms have demonstrated improved performance in hydrological forecasting (Kişi, 2009; Shafaei & Kisi, 2016). More recently, deep learning approaches, including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, have shown promising results in time-series prediction tasks. However, these approaches often require multivariable datasets, extensive hyperparameter tuning, and substantial computational resources, limiting their applicability in data-scarce environments where only historical water level records are available.

To address the challenges of non-stationarity and noise in hydrological data, hybrid approaches combining signal processing techniques with machine learning have emerged as effective solutions. In particular, Wavelet Transform (WT) has proven to be a powerful tool for multi-resolution decomposition of time-series data, enabling the separation of high-frequency fluctuations from low-frequency trends and enhancing model performance (Ramana et al., 2013; Peprah & Larbi, 2021b; Kişi, 2009; Shafaei & Kisi, 2016).

Multivariate Adaptive Regression Splines (MARS), introduced by Friedman (1991), provides a flexible and interpretable machine learning framework capable of modelling complex nonlinear relationships through adaptive basis functions. By incorporating Generalized Cross-Validation (GCV) for model pruning, MARS effectively controls overfitting while maintaining predictive performance. Its successful application in hydrological and environmental modelling further demonstrates its robustness (Yakubu et al., 2018; Kang et al., 2019; Shan-Lin et al., 2016; Demir, 2021).

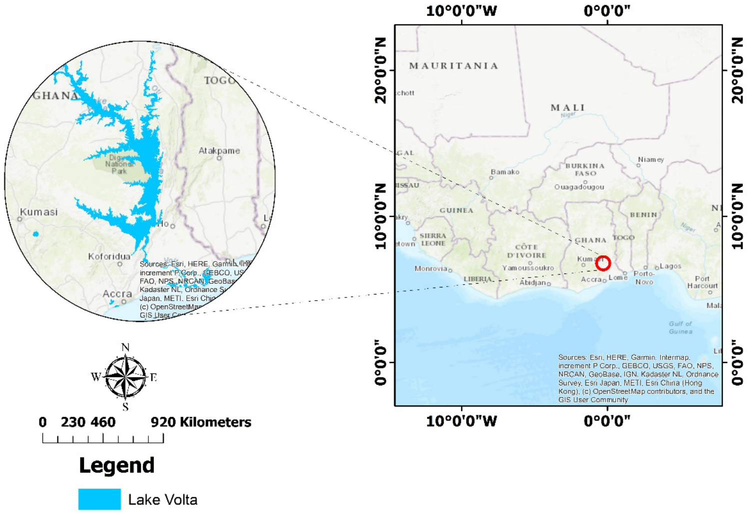
Despite these advancements, most existing studies focus on river discharge modelling or rely on multivariable datasets. There remains a notable gap in the development of single-variable, satellite-altimetry-based forecasting frameworks for large tropical reservoirs operating under data-scarce conditions. Additionally, many previous studies employ random data partitioning strategies, which may lead to inflated performance estimates due to temporal autocorrelation.

This study addresses these limitations by developing and rigorously evaluating a hybrid Discrete Wavelet Transform Neural Network–Multivariate Adaptive Regression Splines (DWTNN–MARS) framework for monthly LWL forecasting in the Lake Volta Basin using 28 years (1992–2020) of satellite altimetry data (Ndehedehe et al., 2017; Coe & Birkett, 2004). The proposed framework integrates wavelet-based signal decomposition, neural network learning for nonlinear feature extraction, and MARS-based adaptive regression to model complex hydrological dynamics. Furthermore, a time-series-aware validation strategy is adopted to ensure robust and unbiased performance evaluation.

The main contributions of this study are threefold. First, it provides a methodologically robust forecasting framework tailored for data-scarce environments. Second, it enhances the modelling of multi-scale hydrological dynamics through a structured decomposition-regression architecture. Third, it ensures reliable predictive assessment through appropriate time-series validation techniques. The findings contribute to advancing data-driven hydrological forecasting and offer practical insights for sustainable reservoir management in large tropical systems.

2. Study area description

Lake Volta (Figure 1), located in Ghana, is the largest artificial reservoir in the world by surface area, covering approximately 8,500 km^2 and representing about 3.2% of the country's total land area (Ndehedehe et al., 2017; Ni et al., 2017). The reservoir plays a central role in national development, supporting hydropower generation, fisheries, irrigation, and regional water security (Peprah & Larbi, 2021a). The hydrological regime of Lake Volta is primarily influenced by seasonal rainfall variability and upstream inflows within the Volta Basin. The region experiences a tropical climate characterized by distinct wet and dry sea-



Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), (c) OpenStreetMap contributors, and the GIS User Community

Figure 1. Map of the Lake Volta Basin showing the study area

sons, resulting in significant seasonal fluctuations in lake water levels. These dynamics reflect the combined effects of climatic forcing and reservoir operation processes.

Monthly Lake Water Level (LWL) data spanning 28 years (October 1992 to September 2020; 336 months) were obtained from satellite altimetry missions, including Topex/Poseidon, Jason-1, and Jason-2/OSTM, provided by the United States Department of Agriculture database (Coe & Birkett, 2004; Ndehedehe et al., 2017). Standard corrections, including atmospheric delay, tidal effects, and altimeter bias adjustments, were applied by the data provider to ensure data accuracy.

Due to the limited availability of consistent long-term hydro-meteorological datasets, such as rainfall, evaporation, and discharge, the basin represents a typical data-scarce environment. Consequently, this study adopts a single-variable forecasting approach based solely on historical LWL records, reflecting realistic operational conditions in many tropical reservoir systems.

3. Methodology

3.1. Data description and pre-processing

Monthly Lake Water Level (LWL) data covering 28 years (October 1992 to September 2020; 336 months) were obtained from satellite altimetry datasets. Before modelling, the data were subjected to pre-processing procedures, including the detection and treatment of missing values, outliers, and structural inconsistencies. A median filtering approach was applied to suppress noise while preserving the inherent seasonal patterns of the time series.

3.2. Methodological framework

The proposed modelling framework (Figure 2) adopts a structured decomposition-regression architecture designed to capture multi-scale hydrological dynamics. The methodology consists of five sequential stages: (i) data pre-processing and computation of monthly mean values, (ii) Discrete Wavelet Transform (DWT) decomposition, (iii) neural network-based nonlinear feature extraction, (iv) Multivariate Adaptive Regression Splines (MARS) modelling, and (v) time-series-aware validation and benchmarking. This integrated approach enhances predictive performance by reducing noise, capturing nonlinear relationships, and controlling model complexity.

3.3. Monthly mean LWL computation

The monthly Mean Lake Water Level (MLWL) was computed from the time-series data using Eq. (1):

$$LWL = \frac{1}{n}\sum_{i=1}^{n} LWL_i, \qquad (1)$$

where: LWL_i represents individual observations, and n denotes the number of observations within a given period. This aggregation ensures consistency in temporal resolution for modelling.

3.4. Discrete Wavelet Transform (DWT) decomposition

Hydrological time series are inherently non-stationary and exhibit multi-scale variability due to climatic forcing and basin dynamics. The Discrete Wavelet Transform (DWT) was therefore employed to decompose the LWL signal into multiple frequency components, enabling simultaneous time-frequency localization and effective noise separation (Ramana et al., 2013; Peprah & Larbi, 2021b). The Daubechies 4 (db4) mother wavelet was selected due to its compact support, orthogonality, and proven effectiveness in hydrological applications. A level-4 decomposition was adopted based on energy distribution analysis, reconstruction error minimization, and Shannon entropy criteria to ensure optimal signal representation. The decomposition resulted in one approximation component (a4), representing long-term trends, and three detail components (d1–d3), capturing high-frequency fluctuations. From a hydrological perspective, the approximation component reflects reservoir storage dynamics, while the detail components represent seasonal variability and short-term responses.

3.5. Neural network modelling

A feedforward neural network was employed to model nonlinear relationships within the decomposed wavelet components. The architecture consisted of an input layer corresponding to the decomposed sub-series, one to two hidden layers with optimized neurons, and an output layer representing the predicted signal. Sigmoid and Rectified Linear Unit (ReLU) activation functions were used to enhance nonlinear mapping capability. Model training was performed using the backpropagation algorithm with early stopping criteria to prevent overfitting and improve gen-

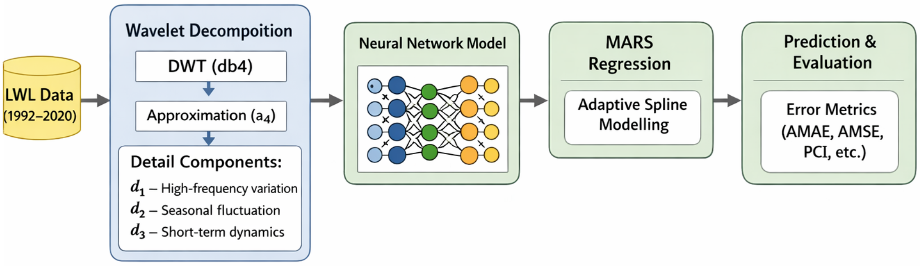


Figure 2. Workflow of the DWTNN-MARS modelling framework

eralization performance. The neural network effectively captured complex interactions across different frequency bands.

3.6. Multivariate Adaptive Regression Splines (MARS)

Multivariate Adaptive Regression Splines (MARS) was applied to further refine the nonlinear relationships extracted by the neural network and enhance predictive generalization. The general MARS formulation is expressed by Eq. (2) as:

$$y_i = \beta_o + \sum_{m=1}^{m} \beta_m B_m\left(x\right) + \varepsilon, \tag{2}$$

where: y_i is the predicted output, $B_m\left(x\right)$ are basis functions, β_m are coefficients, and ε is the error term. The model was configured with a maximum of 21 basis functions during the forward selection phase, with interaction degree limited to 2 to control complexity. Model pruning was conducted using Generalized Cross-Validation (GCV) with a penalty parameter ranging from 2 to 4. A backward elimination process removed insignificant basis functions, thereby reducing overfitting and improving model stability.

3.7. Baseline models for comparative evaluation

To ensure robust benchmarking, two baseline models were implemented. First, an Autoregressive Integrated Moving Average (ARIMA) model was developed, with optimal parameters determined using the Akaike Information Criterion (AIC) and validated through the Augmented Dickey-Fuller (ADF) test. Second, a persistence (naïve) model was used as a reference baseline, defined by Eq. (3) as:

$$Y'_{t+1} = Y_t . \tag{3}$$

This model provides a minimal benchmark for evaluating the predictive skill of more advanced approaches.

3.8. Validation strategy

A time-series-based validation approach was adopted to ensure realistic model evaluation. The dataset was divided chronologically into 70% training and 30% testing subsets, preserving temporal order and preventing data leakage. This approach avoids the overestimation of model performance associated with random data splitting in autocorrelated time series.

3.9. Performance metrics

Model performance was evaluated using multiple statistical indicators, including Arithmetic Mean Absolute Error (AMAE), Arithmetic Mean Square Error (AMSE), Arithmetic Mean Absolute Percentage Error (AMAPE), Arithmetic Standard Deviation (ASD), and Prediction Correction Index (PCI). These metrics provide a comprehensive assessment of prediction accuracy, bias, and variability.

3.10. Overfitting control and reproducibility

Several measures were implemented to ensure model robustness, including wavelet-based denoising, early stopping during neural network training, and GCV-based pruning in the MARS model. Additionally, all models were implemented in MATLAB and Python environments, with fixed random seeds to ensure reproducibility of results.

4. Results and discussion

4.1. Component-level performance

The performance of the MARS model in predicting the decomposed wavelet components is presented in Table 1. During model training, 21 basis functions were initially generated in the forward selection phase for both low-frequency and high-frequency components. Following the backward pruning stage, only a subset of significant basis functions was retained, indicating effective elimination of redundant terms and control of model complexity. Specifically, four basis functions were retained for the approximation component (a4), while [3, 9, 4, and 10] basis functions were retained for the detail components (d1–d4), respectively.

Table 1. Performance metrics for decomposed wavelet components

TRAINING						
PCI	*AMAE*	*AMSE*	*ARMSE*	*AMAPE*	*ASD*	R^2
*a*4	1.6491E-07	0.0013	0.0354	0.0224	4.7731E-05	0.9996
*d*1	2.0400E-09	0.2387	0.4885	1.3796	0.0006	0.4984
*d*2	3.7500E-08	0.0519	0.2278	0.7755	0.0003	0.6950
*d*3	2.6700E-07	0.0533	0.2308	0.0172	0.0001	0.9529
*d*4	1.4200E-07	0.0030	0.0545	0.0454	0.0004	0.9919
TESTING						
PCI	*AMAE*	*AMSE*	*ARMSE*	*AMAPE*	*ASD*	R^2
*a*4	0.0005	0.0004	0.0200	0.0106	0.0003	0.9999
*d*1	0.0192	0.1271	0.3566	0.5170	0.0027	0.5359
*d*2	0.0085	0.0405	0.2013	0.4212	0.0011	0.6200
*d*3	0.0233	0.0370	0.1924	0.0638	0.0034	0.9358
*d*4	0.0005	0.0025	0.0504	0.0080	0.0003	0.9884

The results show that the model achieved very low error values and high coefficients of determination (R^2) across both training and testing phases, indicating strong agreement between observed and predicted component values. The low-frequency approximation component (a4), which represents long-term storage trends, exhibited near-perfect predictive performance due to its smooth and noise-reduced nature. In contrast, higher-frequency components displayed slightly higher error values, reflecting the increased complexity associated with short-term variability. Overall, the results confirm that wavelet decomposition significantly enhances model performance by isolating multi-scale patterns and reducing noise effects.

4.2. Overall model performance

The overall predictive performance of the reconstructed LWL signal is summarized in Table 2, which presents a comparative evaluation of the proposed DWTNN–MARS model, the DWTNN–ARIMA benchmark model.

Table 2. Comparative performance of DWTNN–MARS and benchmark models for monthly LWL prediction

Model	AMAE (m)	AMSE (m^2)	AMAPE (%)	ASD (m)	PCI (m)
DWTNN–ARIMA	0.0960	0.0041	9.54	0.0420	0.2152
DWTNN–MARS	0.0730	0.0032	7.68	0.0340	0.0215

The results demonstrate that the DWTNN–MARS model consistently outperforms both benchmark models across all evaluation metrics. Specifically, the proposed model achieves lower prediction errors (AMAE, AMSE, AMAPE), reduced residual dispersion (ASD), and significantly lower prediction bias (PCI). These results confirm the superior predictive capability and stability of the hybrid DWTNN–MARS framework.

4.3. Graphical analysis

Graphical comparisons (Figure 3) between observed and predicted LWL values further validate the model performance.

The line graph demonstrates a close agreement between observed and predicted values, indicating that the model effectively captures both seasonal fluctuations and long-term trends. Figure 4 is the Box plot comparison of prediction errors for DWTNN–ARIMA and DWTNN–MARS.

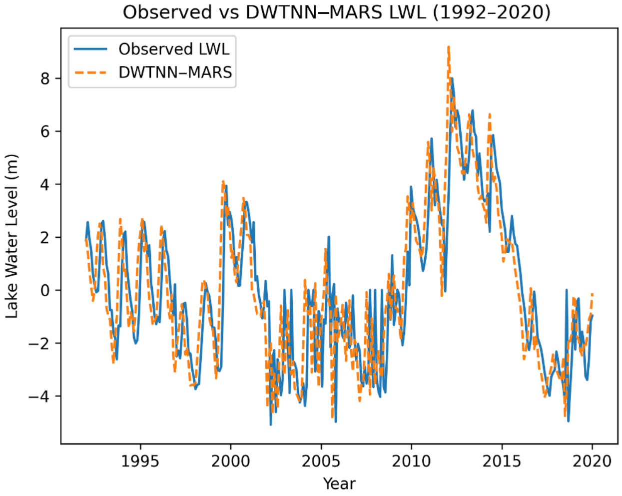


Figure 3. Observed and predicted monthly lake water levels using the DWTNN–MARS model

The box plot reveals that the DWTNN–MARS model exhibits lower median error, reduced variability, and fewer extreme deviations compared to the DWTNN–ARIMA model, confirming its improved predictive consistency.

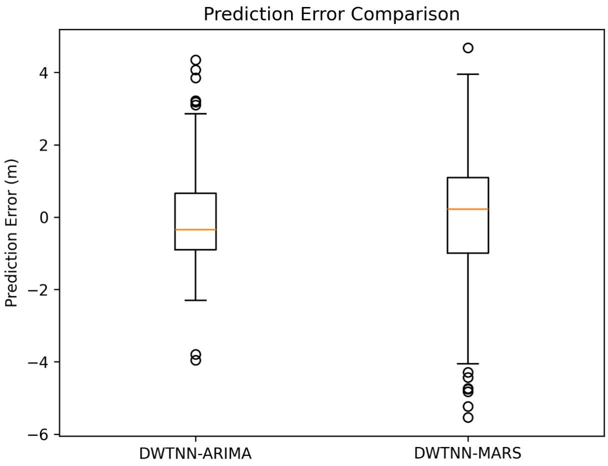


Figure 4. Box plot comparison of prediction errors for DWTNN–ARIMA and DWTNN–MARS models

4.4. Discussion

The results highlight the effectiveness of the hybrid DWTNN–MARS framework in modelling non-stationary hydrological time series. The superior performance of the model can be attributed to the complementary strengths of its components. Wavelet decomposition enhances signal quality by separating low-frequency trends from high-frequency noise, thereby simplifying the modelling process. The neural network component captures nonlinear relationships within the decomposed sub-series, while the MARS model provides flexible, adaptive regression capable of modelling complex interactions.

The extremely low residual dispersion (ASD = 0.0003 m) and low prediction bias (PCI = 0.0215 m) observed for the DWTNN–MARS model indicate a highly stable and reliable prediction framework. In contrast, the DWTNN–ARIMA model exhibits higher variability and bias, reflecting its limited ability to capture nonlinear and multi-scale dynamics.

From a hydrological perspective, the decomposition of the LWL signal into approximation and detail components allows for a clearer interpretation of system dynamics. The approximation component captures long-term storage behaviour, while the detail components represent seasonal variability driven by rainfall and inflow processes. This multi-scale representation improves both model interpretability and predictive accuracy.

Furthermore, compared to deep learning approaches such as LSTM and GRU, which require large multivariable datasets, the proposed framework demonstrates that high predictive performance can be achieved using a single-variable dataset when combined with appropriate signal processing and hybrid modelling techniques. This makes the approach particularly suitable for data-scarce tropical environments.

5. Conclusions and recommendations

5.1. Conclusions

This study developed and evaluated a hybrid Discrete Wavelet Transform Neural Network–Multivariate Adaptive Regression Splines (DWTNN–MARS) framework for monthly Lake Water Level (LWL) forecasting in the Lake Volta Basin using 28 years (1992–2020) of satellite altimetry data. The results demonstrate that the proposed model achieves high predictive accuracy, with a Prediction Correction Index (PCI) of 0.0215 m and an Arithmetic Standard Deviation (ASD) of 0.0003 m, indicating minimal prediction bias and tightly clustered residual errors. In comparison, the benchmark DWTNN–ARIMA model exhibited higher prediction bias (PCI = 0.2152 m) and greater residual variability (ASD = 0.0420 m).

These findings confirm that the integration of wavelet-based signal decomposition, neural network learning, and adaptive spline regression significantly enhances the modelling of non-stationary hydrological time series. The structured decomposition–regression architecture effectively captures both seasonal variability and long-term storage dynamics, while maintaining model interpretability and stability. Overall, the study demonstrates that reliable and accurate forecasting can be achieved using a single-variable dataset when combined with appropriate hybrid modelling techniques, making the approach particularly suitable for large tropical reservoirs operating under data-scarce conditions.

5.2. Limitations of the study

Despite the strong performance of the proposed framework, several limitations should be acknowledged. First, the study relies exclusively on single-variable LWL data, which may not fully capture the influence of key hydro-climatic drivers such as rainfall, evaporation, and inflow dynamics. Second, the absence of multi-source hydro-meteorological datasets limits the model's ability to explicitly represent physical processes governing lake water level fluctuations. Third, the performance of the model may be sensitive to the choice of wavelet type and decomposition level, which could influence the quality of signal representation and subsequent predictions. These limitations highlight areas for further refinement and model enhancement.

5.3. Recommendations

Future research should focus on extending the proposed framework to improve its applicability and robustness. Specifically, the integration of multi-source datasets, including hydro-meteorological variables such as rainfall, temperature, evaporation, and discharge, is recommended to enhance physical interpretability and predictive performance. Additionally, the exploration of advanced deep learning architectures, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, may provide further improvements in capturing complex temporal dependencies. Finally, the development of real-time or near-real-time forecasting systems, coupled with operational decision-support tools, would enhance the practical utility of the model for reservoir management and water resource planning in data-limited environments.

Acknowledgements

The authors appreciate the anonymous reviewer's constructive criticism, time, and effort in helping to make this paper better.

Authors contribution

M. S. P. is responsible for the conceptualization, writing the initial manuscript and building the Wavelet Neural Network model. E. K. L. is responsible for the conceptualization, proofreading of the manuscript and building of the MARS model. P. O. A. is responsible for proofreading, and models evaluation, building the ARIMA model and validation assessment.

Disclosure statement

The authors declare that there is no potential conflict of interest in this work. The work does not infringe any copyright, proprietary right, or any other right of any third party, and the authors are the sole owners of the work.

References

Aksoy, H., Unal, N. E., Eris, E., & Yuce, M. I. (2013). Stochastic modelling of Lake Van water level time series with jumps and multiple trends. *Hydrology and Earth System Sciences*, *17*(6), 2297–2303. https://doi.org/10.5194/hess-17-2297-2013

Coe, M. T., & Birkett, C. M. (2004). Calculation of river discharge and prediction of lake height from satellite radar altimetry: Example for the lake Chad basin. *Water Resources Research*, *40*(10), Article W10205. https://doi.org/10.1029/2003WR002543

Demir, V. (2021). E*nhancing monthly lake levels forecasting using heuristic regression techniques with periodicity data component: Application of lake Michigan.* Research Square. https://doi.org/10.21203/rs.3.rs-726003/v1

Doğan, E., Kocamaz, U. E., Utkucu, M., & Yildirim, E. (2016). Modelling daily water level fluctuations of Lake Van (Eastern Turkey) using artificial neural networks. *Fundamental and Applied Limnology*, *187*(3), 177–189. https://doi.org/10.1127/fal/2015/0736

Friedman, J. H. (1991). Multivariate adaptive regression splines. *Annals Statistics*, *19*, 1–67. https://doi.org/10.1214/aos/1176347963

Huang, A., Rao, Y. R., Lu, Y., & Zhao, J. (2010). Hydrodynamic modelling of Lake Ontario: An intercomparison of three models. *Journal of Geophysical Research*: *Oceans*, *115*(C12), Article C12076. https://doi.org/10.1029/2010JC006269

Kakahaji, H., Banadaki, H. D., Kakahaji, A., & Kakahaji, A. (2013). Prediction of Urmia Lake water-level fluctuations by using analytical, linear statistics and intelligent methods. *Water Resource Management*, *27*, 4469–4492. https://doi.org/10.1007/s11269-013-0420-2

Kang, F., Liu, X., & Li, J. (2019). Concrete dam behaviour prediction using multivariate adaptive regression splines and measured air temperature. *Arabian Journal for Science and Engineering*, *44*, 8661–8673. https://doi.org/10.1007/s13369-019-04095-z

Kebede, S., Travi, Y., Alemayehu, T., & Marc, V. (2006). Water balance of Lake Tana and its sensitivity to fluctuations in rainfall, Blue Nile basin, Ethiopia. *Journal of Hydrology*, *316*(1–4), 233–247. https://doi.org/10.1016/j.jhydrol.2005.05.011

Khatibi, R., Ghorbani, M. A., Naghipour, L., Jothiprakash, V., Fathima, T. A., & Fazelifard, M. H. (2014). Inter-comparison of time series models of lake levels predicted by several modelling strategies. *Journal of Hydrology*, *511*, 530–545. https://doi.org/10.1016/j.jhydrol.2014.01.009

Kişi, Ö. (2009). Neural network and wavelet conjunction model for modelling monthly level fluctuations in Turkey. *Hydrological Processes*, *23*(14), 2081–2092. https://doi.org/10.1002/hyp.7340

Mislan, Gaffar, A. F. O., Havluddin, & Puspitasari, N. (2018). Water level prediction of lake cascade Mahakam using adaptive neural network backpropagation (ANNBP). *IOP Conference Series*: *Earth and Environmental Science*, *144*, Article 012009. https://doi.org/10.1088/1755-1315/144/1/012009

Ndehedehe, C. E., Awange, J. L., Kuhn, M., Agutu, N. O., & Fukuda, Y., (2017). Analysis of hydrological variability over the Volta River basin using in-situ data and satellite observations. *Journal of Hydrology*: *Regional Studies*, *12*, 88–110. https://doi.org/10.1016/j.ejrh.2017.04.005

Ni, S., Chen, J., Wilson, C. R., & Hu, X. (2017). Long-term water storage changes of Lake Volta from GRACE and satellite altimetry and connections with regional climate. *Remote Sensing*, *9*(8), Article 842. https://doi.org/10.3390/rs9080842

Peprah, M. S., & Larbi, E. K. (2021a). Lake water level prediction model based on autocorrelation regressive integrated moving average and Kalman filtering techniques – an empirical study on Lake Volta basin, Ghana. *International Journal of Earth Sciences Knowledge and Applications*, *3*(1), 1–11.

Peprah, M. S., & Larbi, E. K. (2021b). Lake water level prediction model based on artificial intelligence and classical techniques – an empirical study on Lake Volta basin, Ghana. *International Journal of Earth Sciences Knowledge and Applications*, *3*(2), 134–150.

Piasecki, A., Jurasz, J., & Skowron, R. (2017). Forecasting surface water level fluctuations of Lake Serwy (Northeastern Poland) by artificial neural networks and multiple linear regression. *Journal of Environmental Engineering and Landscape Management*, *25*(4), 379–388. https://doi.org/10.3846/16486897.2017.1303498

Ramana, R. V., Krishna, B., Kumar, S. R., & Pandey, N. G. (2013). Monthly rainfall prediction using wavelet neural networks analysis. *Water Resource Management*, *27*, 3697–3711. https://doi.org/10.1007/s11269-013-0374-4

Shafaei, M., & Kisi, O. (2016). Lake level forecasting using wavelet-SVR, wavelet-ANFIS and wavelet-ARMA conjunction models. *Water Resources Management*, *30*, 79–97. https://doi.org/10.1007/s11269-015-1147-z

Shan-Lin, T., Cheng-Feng, C., Yang-Ling, B., Wen-Juan, Z., Yu, S., & En, H. (2016). Application of multivariate adaptive regression spline models in long term prediction of river water pollution. *Taiwan Water Conservancy*, *64*(4), 72–80.

Yakubu, I., Ziggah, Y. Y., & Peprah, M. S. (2018). Adjustment of DGPS Data using artificial intelligence and classical least square techniques. *Journal of Geomatics*, *12*(1), 13–20.

Young, C.-C., Liu, W.-C., & Hsieh, W.-L. (2015). Predicting the water level fluctuation in an Alpine Lake using physically based, artificial neural network, and time series forecasting models. *Mathematical Problems in Engineering*, Article 708204. https://doi.org/10.1155/2015/708204

Zhu, S., Hrnjica, B., Ptak, M., Choinski, A., & Sivakumar, B. (2020). Forecasting of water level in multiple temperate lakes using machine learning models. *Journal of Hydrology*, *585*, Article 124819. https://doi.org/10.1016/j.jhydrol.2020.124819