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Forecasting Water Level of the Vietnamese Mekong Delta Integrating the Harmonic Tidal Method and Deep Learning Model

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Abstract

Hourly Water Level Forecasting (HWLF) is essential for flood management and disaster mitigation in hydrodynamically complex regions like the Vietnamese Mekong Delta (VMD). Here, we benchmarked a Long Short-Term Memory (LSTM) network for HWLF at the My Thuan station on the Tien River, a location influenced by both river and tidal dynamics. Using an hourly dataset from 1978 to 2022, we compared the LSTM model's predictions against the traditional harmonic analysis method for lead times of 1 to 168 hours. A sensitivity analysis showed that an input sequence of 360 past hourly observations (15 days) was optimal. The LSTM model performed well at short lead times, with a NASH index of 0.98 and an RMSE of 9.25 cm for a 1-hour forecast. However, its accuracy decreased significantly at longer horizons; the NSE dropped to 0.59 and the RMSE exceeded 48 cm at 168 hours. Despite this, the LSTM model was consistently better than the harmonic method, especially at capturing the non-linear interactions between river discharge and tides. Our results provide a

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clear performance baseline for a univariate deep learning model in this region, defining its operational limits. While LSTM is promising for short-term forecasts, our findings show that external physical data is needed to improve long-term reliability.

Keywords: Deep learning, Tien River, Harmonic analysis, Time-series analysis, Water level forecast.

1. INTRODUCTION

The VMD is a region of immense strategic importance, underpinning Vietnam's food security and driving its socio-economic development. It is home to approximately 18 million people and accounts for over 50% of the nation's rice production and 90% of its rice exports [1, 2]. However, this vital region faces a confluence of severe hydrological threats, primarily recurrent floods and intensifying droughts, which exert significant pressure on agriculture, infrastructure, and livelihoods [3]. Floods, in particular, have historically had a profound impact, causing extensive crop damage, accelerating riverbank erosion, and posing a direct risk to human life. The catastrophic 2000 flood, for example, resulted in economic losses estimated at nearly 1 billion USD and underscored the region's vulnerability to extreme hydrological events [4, 5]. Conversely, recent droughts, such as those in 2015–2016 and 2019–2020, have led to widespread saline intrusion, disrupting agricultural cycles and threatening the freshwater supply for millions [6, 7]. These challenges are projected to be exacerbated by climate change, which is anticipated to intensify extreme flow conditions and further elevate the frequency and severity of both floods and droughts [8].

In response to these escalating risks, the development of robust predictive tools for water resource management has become a critical priority. The ability to accurately forecast water levels, especially at hourly timescales, is fundamental for optimizing flood mitigation strategies, managing salinity intrusion, and minimizing risks across the basin [9]. Traditional approaches to hydrological forecasting have largely relied on physically-based numerical models (e.g., SWAT, HEC-RAS, MIKE 11) [10]. These models simulate complex physical processes by solving mathematical equations governing mass, momentum, and energy conservation. While they offer detailed insights into site-specific hydrological dynamics [11], their application in real-time forecasting is often hampered by significant challenges. These include intensive data requirements for calibration and validation, high computational costs, and difficulties in obtaining timely field data, which can compromise prediction accuracy [12]. Furthermore, in tidally influenced deltas like the VMD, water level fluctuations are driven by a complex interaction of river discharge, ocean tides, and non-linear factors, which have been altered by upstream dam regulation and geomorphological changes. Conventional numerical and stationary harmonic models often struggle to fully capture these non-linearities, limiting their predictive precision [13, 14].

Data-driven modeling offers a flexible alternative to physically-based approaches. These models, using statistical, machine learning (ML), and deep learning (DL) techniques, can identify complex, non-linear patterns in historical time-series data without needing to explicitly model the underlying physics [15, 16]. This approach has been applied in various forms, such as combining machine learning with traditional statistical models like ARIMA to improve forecast accuracy [17]. Deep learning, a subfield of ML using multi-layered neural networks, has shown strong potential in hydrology [18] and has been implemented in early warning systems in other complex river basins [19]. Models like the LSTM network, making them suitable for time-series forecasting [20, 21].

A growing body of literature has demonstrated the high accuracy of DL models in water level and streamflow prediction globally. For instance, Atashi et al. [22] successfully applied LSTM to forecast water levels in the Red River of the North from six hours to one week in advance, demonstrating its superiority over classical statistical and ML models. Similarly, studies in various hydrological settings have validated the reliability of AI-based techniques for short-term (1–6 hours) [23], mid-term (up to 36 hours) [24], and long-term forecasting, consistently showing improvements in accuracy over traditional methods. Within Vietnam, AI-driven models have been applied to various river basins, confirming their utility. For example, LSTM and Gated Recurrent Unit (GRU) models have been used to forecast flood events in the Ca River Basin [25], while Wavelet-ANN hybrids have improved short-term forecasts in the Red River Delta [26]. However, research on high-resolution, HWLF within the VMD remains relatively limited, with most studies focusing on daily predictions [27, 28]. The performance capabilities and, more importantly, the inherent limitations of standard deep learning architectures for hourly forecasting in this unique fluvial-tidal environment have not yet been rigorously quantified.

This study aims to address this research gap by conducting a comprehensive benchmark analysis of a deep learning model, focused on the LSTM architecture, for HWLF in the VMD. By applying the model to a multi-decade dataset from a station subject to both riverine and tidal influences, we seek to rigorously quantify its baseline performance and its limitations across a wide range of forecast horizons (from 1 to 168 hours). To contextualize its performance, we conduct a direct comparison with the traditional harmonic analysis method.

2. MATERIALS AND METHODS

2.1 Research Design

The Mekong River, one of the world's major river systems, originates on the Tibetan Plateau and flows through six countries before entering the VMD in southern Vietnam (FIGURE 1). The VMD is a vast, low-lying plain covering over four million hectares, characterized by a dense network of rivers and canals nourished by the Tien and Hau Rivers, the two main distributaries of the Mekong [1]. The region's hydrology is governed by two distinct seasons, leading to seasonal flooding, and a dry season characterized by minimal precipitation and risks of saline intrusion. Water level fluctuations are primarily driven by the combined effects of upstream freshwater discharge from the Mekong River, partly regulated by the Tonle Sap Lake in Cambodia, and strong tidal influences from the East Sea [29]. This complex interaction makes accurate water level forecasting a significant scientific challenge.

2.2 Selections of Stations and Approaches

To capture the varying hydrological regimes across the delta, water level data were considered from three key stations along the Tien River: Tan Chau (upstream, primarily river-influenced), My Thuan (mid-delta, a transitional zone influenced by both river discharge and tides), and Vam Kenh (river-mouth, primarily tide-influenced) (FIGURE 1, TABLE 1). For this pilot study, the My Thuan station was selected for detailed analysis and LSTM model development, as its location represents the complex interplay of forces that forecasting models must capture. Stationary harmonic analysis was then performed for all three stations to provide a baseline for comparison, representing the traditional approach to predicting tidally driven water levels.

2.3 LSTM Model Development

Hourly water level observations from the My Thuan station, spanning the period from 1978 to 2022, were used.

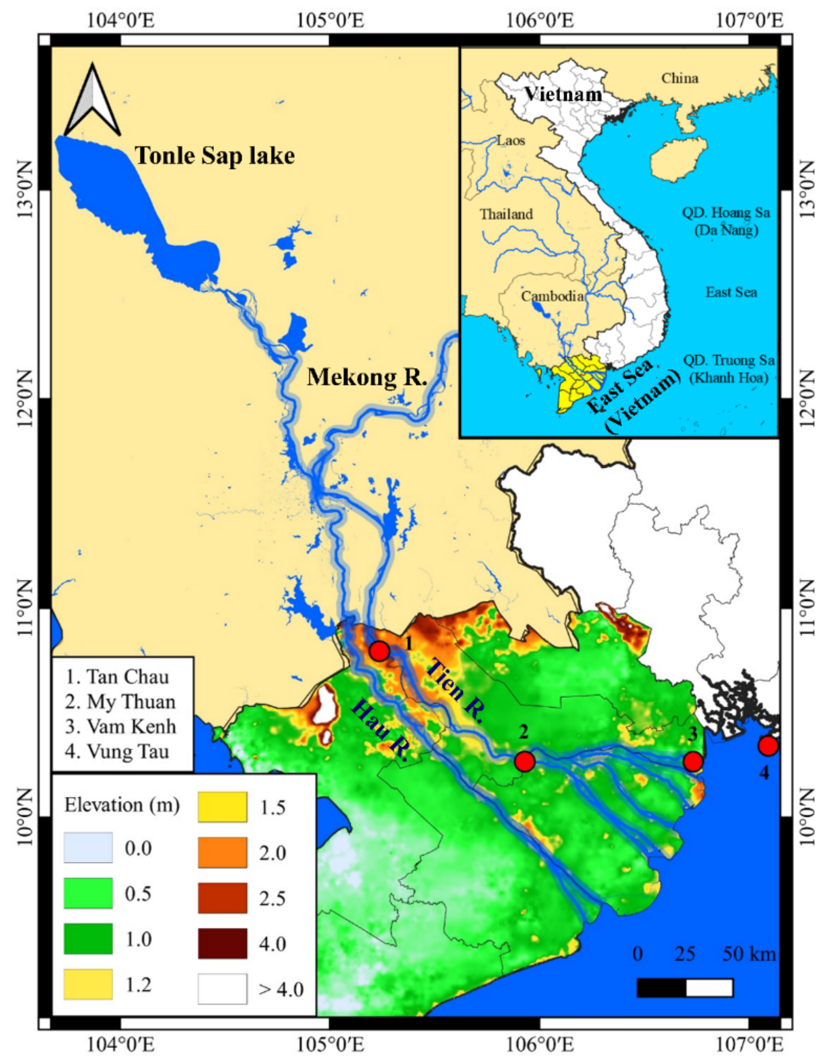

Figure 1: Maps of study area and locations of water level stations (numbered from 1 to 4) used for this study. Elevations data for the Vietnamese Mekong Delta [30].

Table 1: Water level datasets used for the analyses at hydrological stations along the Tien River and a reference station (Vung Tau) at open sea.

Name	River	Latitude	Longitude	Distance from river mouth (km)	Duration (year)
Tan Chau	Tien	10.800556	105.247778	197	1978-2022
My Thuan	Tien	10.275000	105.926389	88	1978-2022
Vam Kenh	Tien	10.274444	106.737222	4	1979–2022
Vung Tau	East Sea	10.339444	107.071111	-	1980-2024

The dataset was divided into two distinct subsets:80% and 20% of the data were used for training and validation, respectively.

To improve the training stability and convergence of the neural network, the raw data were normalized to a range of [0, 1] using the MinMaxScaler function. The scaler was fitted only on the training data and then used to transform the validation and testing sets to prevent data leakage.

The choice of input sequence length (input lag) is a critical hyperparameter that determines how much historical information the model uses for prediction. To identify an optimal lag, a sensitivity analysis was performed. Several lag periods were tested (e.g., 168, 360, 504, and 720 hours). For each lag, a model was trained and evaluated on the validation set for a 24-hour forecast horizon. The analysis revealed that performance improved significantly up to a lag of 360 hours, after which the gains became marginal while the computational cost increased substantially. Therefore, a fixed input sequence of 360 antecedent hourly water levels was selected as the optimal trade-off between performance and efficiency for all forecast horizons.

We designed our LSTM model with two sequential LSTM layers. The first layer had 100 units and was configured with return-sequences = True to pass its full output to the next layer, which contained 50 units. To help prevent overfitting, we added a Dropout layer with a 0.2 rate after each LSTM layer. Following these blocks, we used a Dense layer of 25 neurons with ReLU activation, and a final single-neuron Dense layer generated the water level prediction. We selected this architecture after initial tests on the validation set showed it offered a good trade-off between model complexity and performance for our time-series data.

We compiled the model using the Adam optimizer and set mean squared error (MSE) as the loss function. The model was trained for up to 200 epochs with a batch size of 8. To avoid overfitting, we employed an EarlyStopping callback which halted the training if the validation loss failed to improve for 10 consecutive epochs, restoring the model weights from the best epoch. After training, predictions were scaled back to their original values for evaluation. We then assessed the model's performance using four standard metrics: NASH index, Kling-Gupta efficiency (KGE), mean absolute error (MAE), and root mean squared error (RMSE).

2.4 Harmonic Analysis Method

Harmonic analysis is a classical method used to predict tidal water levels by decomposing a time series into a finite sum of sinusoidal components (tidal constituents), each with a specific amplitude and frequency (e.g., [31]). The method assumes that water level variations are a combination of these predictable periodic signals. The fundamental equation for harmonic analysis is expressed as:

Basically, harmonic analysis is expressed as:

$$y\,(t) = Z(t) + \sum_{i=1}^{N} A_i \cos\,(\omega_i t - \psi_i)) \tag{1}$$

Where: y(t) is the water level time-series; Z(t) is the mean water level which is possible changes in time. This is in fact due to a change in relative sea/water level induced by climatic or anthropogenic forces.

A_i is the amplitude of the i^{th} tidal constituent; ω_i is the angular frequency of the i^{th} tidal constituent (related to its period), ϕ_i is the phase, or phase lags for the i^{th} harmonic, indicating when the constituent reaches its peak value. N is the number of tidal constituents being analyzed.

This method was applied to the datasets from Tan Chau, My Thuan, and Vam Kenh to generate predicted water level time series for comparison with the LSTM model results.

3. RESULTS AND DISCUSSION

3.1 Training Convergence of the LSTM Model

The convergence behavior of the LSTM model during training provides initial insights into its ability to learn from the data. FIGURE 2 illustrates the training and validation loss (MSE) curves over 200 epochs.

For the 1-hour forecast, the training and validation losses decrease rapidly and converge to a low value with a minimal gap, indicating an effective fit without significant overfitting. For longer horizons, such as the 144-hour and 168-hour forecasts, a clear discrepancy emerges. While the training loss steadily decreases, the validation loss plateaus and begins to show volatility, signaling the onset of overfitting. The EarlyStopping mechanism was crucial in these cases, terminating training before the model began to memorize noise from the training set, thus ensuring better generalization to unseen data. The use of Dropout layers also contributed to regularizing the model. However, the persistent gap at longer horizons suggests that even with these techniques, the inherent lack of predictive information in the univariate time-series limits the model's ability to generalize over extended periods.

3.2 Long Short-Term Model Performance

The quantitative performance of the LSTM model across all eight forecast horizons is summarized in TABLE 2 and visualized in FIGURES 3. The results clearly demonstrate that the model's performance is highest at shorter lead times and degrades progressively as the forecast horizon increases. At the 1-hour horizon, the model achieves excellent performance, with an NSE of 0.98 and a KGE of 0.92. These values indicate a very strong agreement between observed and predicted

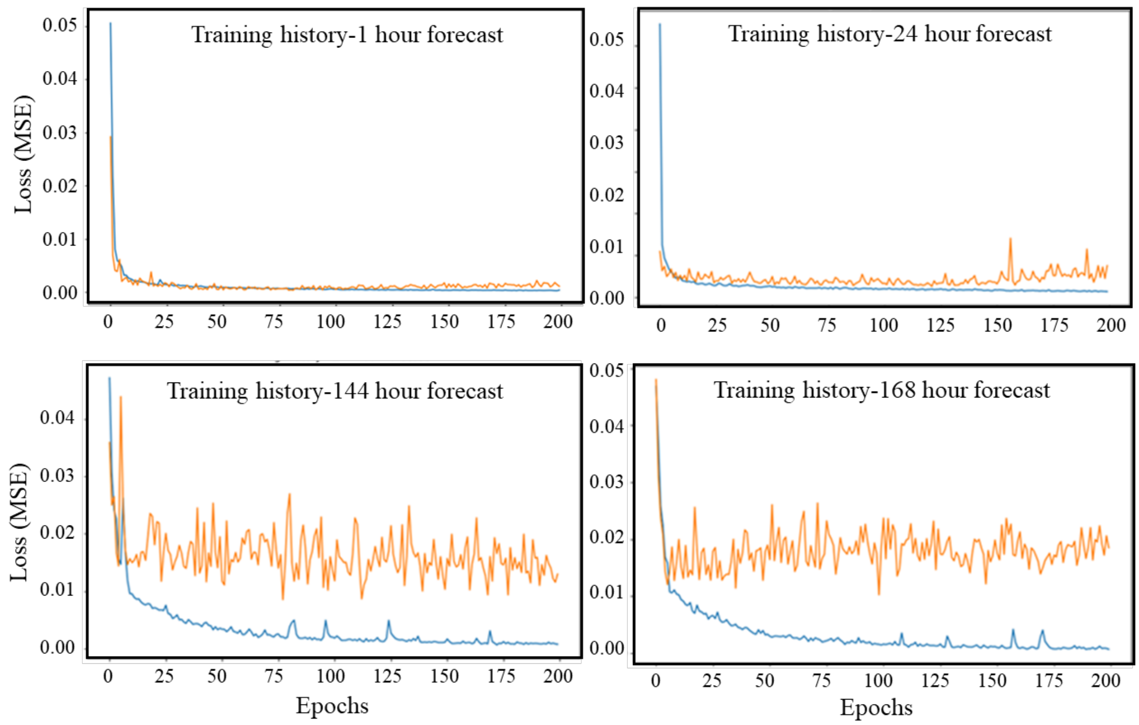

Figure 2: Training and test losses of the LSTM model for 1-hour, 24-hour, 144-hour, and 168-hour forecast horizons

water levels. The corresponding MAE and RMSE are low, at 7.55 cm and 9.25 cm, respectively, signifying high forecasting accuracy. Performance remains robust at the 24-hour horizon, with NSE and KGE values of 0.97 and 0.98, and only a moderate increase in MAE (9.54 cm) and RMSE (12.57 cm). Beyond 24 hours, the model's performance begins to degrade more significantly. By 72 hours (3 days), the NSE has decreased to 0.87, and the RMSE has more than doubled to 27.05 cm. This reflects the inherent difficulty in capturing the long-term dynamics of hourly water level fluctuations from the time-series data alone. The deterioration becomes even more pronounced for horizons beyond 96 hours. At 168 hours (7 days), the NSE and KGE values fall to 0.59 and 0.75, respectively, indicating a substantial loss of predictive power. The MAE and RMSE increase to 37.01 cm and 48.21 cm, highlighting the limitations of this baseline LSTM model for maintaining high accuracy over extended forecast periods.

3.3 Analysis of Prediction Accuracy Across Water Level Ranges

The scatter plots in FIGURE 4, show the model's performance across different water levels. For short horizons (1 and 24 hours), the predicted and observed values align closely with the 1:1 line, confirming the high accuracy reported in TABLE 2 (Pearson's r = 0.99 for both). However, we observed a slight tendency to overpredict low water levels, a challenge also noted in other studies

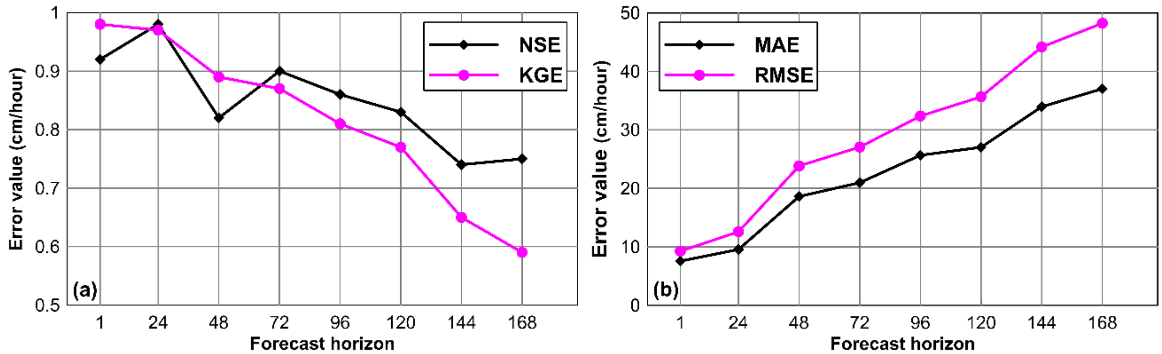

Figure 3: a) Error and b) metric values of the LSTM model across different forecasts.

focused on low-flow forecasting using LSTM [32]. Conversely, the model slightly underpredicted high water levels (>160 cm). This underestimation of flood peaks is an important factor for operational warning systems, but the model's high overall accuracy makes it reliable for short-term flood alerts and tidal gate management.

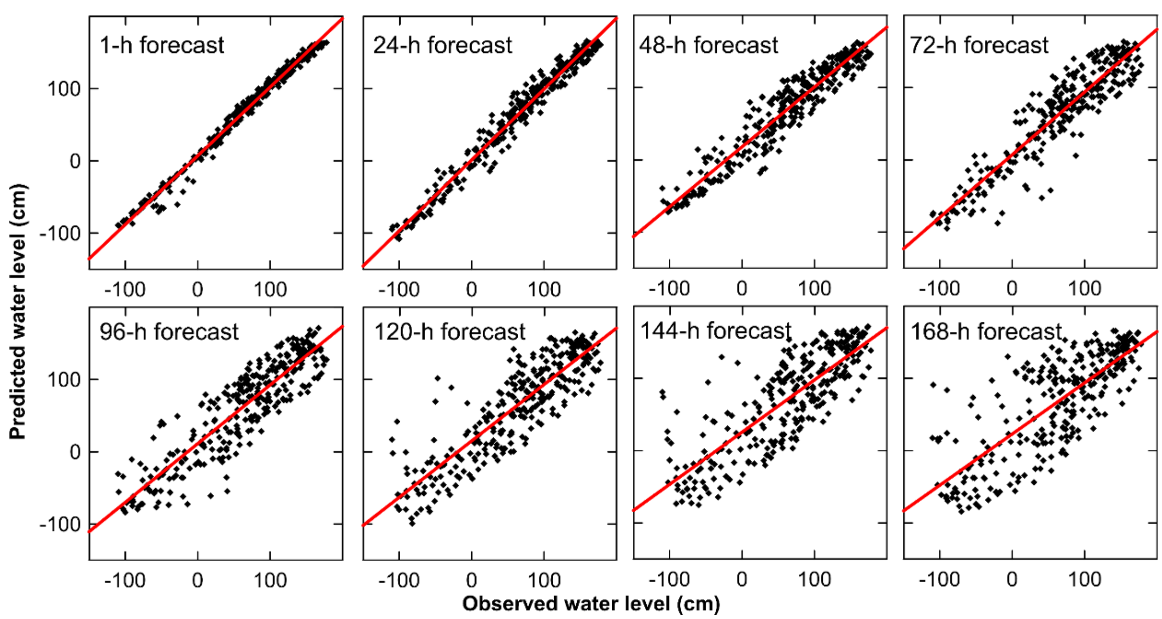

Figure 4: comparison between observed and predicted water levels at different forecast horizons.

As the forecast horizon extends to 48 and 72 hours, the dispersion of the data points increases, indicating rising predictive uncertainty. The biases become more apparent: low levels are more consistently overpredicted, while high water levels are more frequently underpredicted. At long horizons (96 hours and beyond), the forecast performance deteriorates significantly. The scatter becomes highly dispersed across all water level ranges, and the relationship between predicted and observed values grows increasingly inconsistent. These limitations substantially reduce the model's suitability for operational hydrological forecasting at lead times of four days or more.

Table 2: Preliminary Performance of the LSTM Model Across Different Forecast Horizons

Time (hour)	NSE	KGE	MAE (cm/hour)	RMSE (cm/hour)
1	0.98	0.92	7.55	9.25
24	0.97	0.98	9.54	12.57
48	0.89	0.82	18.60	23.82
72	0.87	0.90	20.96	27.05
96	0.81	0.86	25.65	32.35
120	0.77	0.83	27.01	35.64
144	0.65	0.74	33.94	44.15
168	0.59	0.75	37.01	48.21

3.4 Time-Series Comparison and Tidal Pattern Capture

A visual comparison of the predicted and observed time-series (FIGURE 5) further elucidates the model's capabilities. At short-term horizons (1 and 24 hours), the predicted (red) and observed (blue) water levels exhibit strong alignment. The model successfully captures the defining double-peak and double-trough pattern of the mixed semi-diurnal tides at My Thuan, with minimal phase shifts or amplitude errors. This demonstrates its effectiveness in modeling high-frequency water level dynamics, making it suitable for applications requiring precise timing, such as sluice gate management for salinity control.

At the 48-hour horizon, a gradual decline in accuracy is visible. While the model still captures the overall tidal cycle, it begins to underestimate peak levels and overestimate troughs. Furthermore, a noticeable temporal misalignment (phase shift) emerges, particularly for secondary peaks and troughs. At horizons exceeding 96 hours, these issues become more severe, with increasing phase shifts and reduced accuracy in capturing the magnitude of tidal peaks and troughs. This indicates a key limitation in its reliability for supporting rapid-response strategies at longer lead times.

3.5 Comparison with Harmonic Analysis

Finally, we compared the LSTM model's predictions to those from the traditional harmonic analysis method. Harmonic analysis produced high statistical correlations at all three stations (Pearson r = 0.90 for Tan Chau, 0.93 for My Thuan, and 0.98 for Vam Kenh). However, as shown in FIGURE 6, this method struggled to predict water level amplitudes accurately at upstream locations like Tan Chau, where river discharge creates strong non-linear effects. This limitation is a known issue in tidal rivers, where phenomena like the reversal of low water levels cannot be captured by stationary harmonics alone **[33]**. The harmonic predictions were much closer to the observed data at the river mouth (Vam Kenh), where the tidal signal is the primary driver.

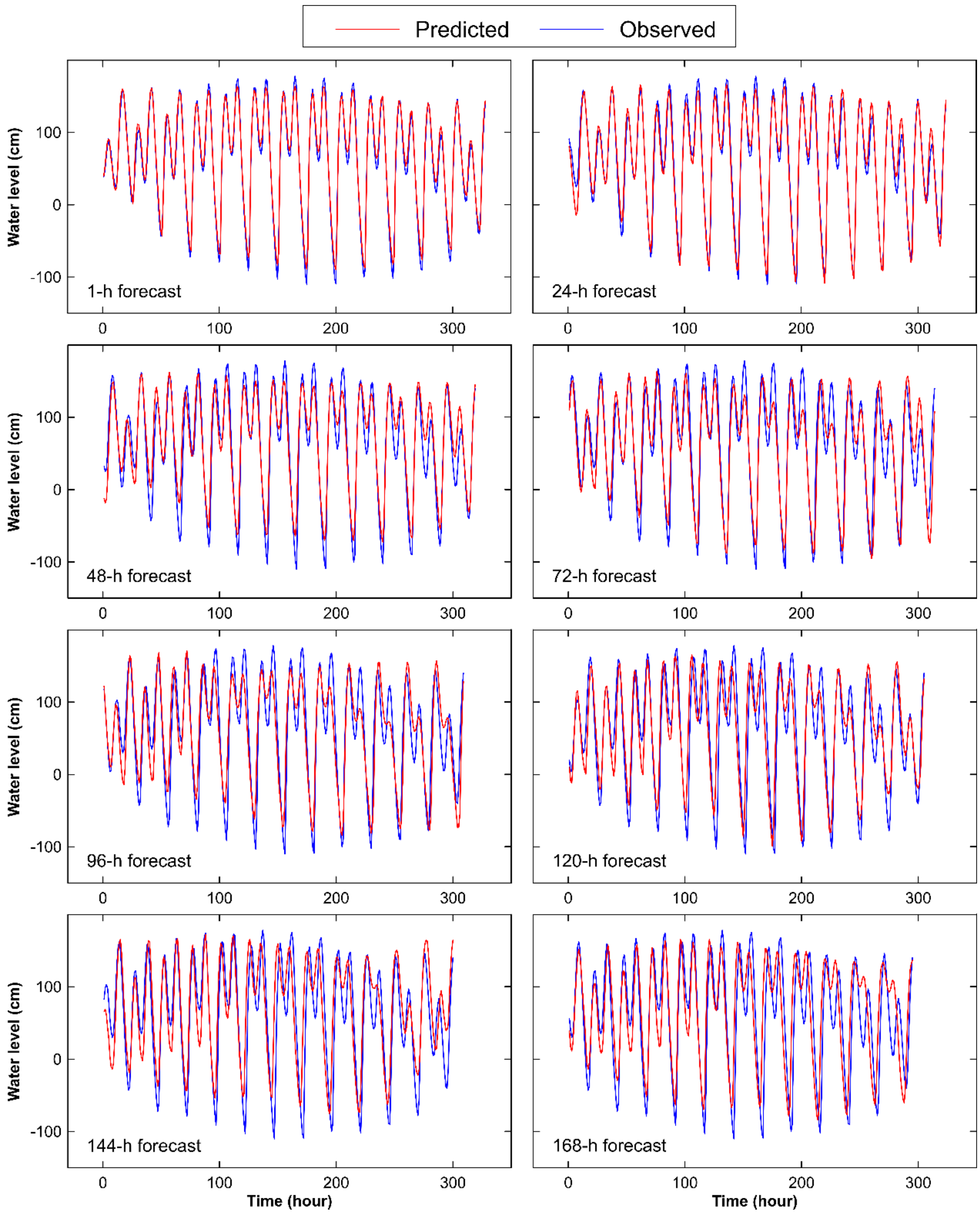

Figure 5: Time-series plot of hourly observed vs. predicted water levels at different forecast times (at hour scale from 18 December 2022).

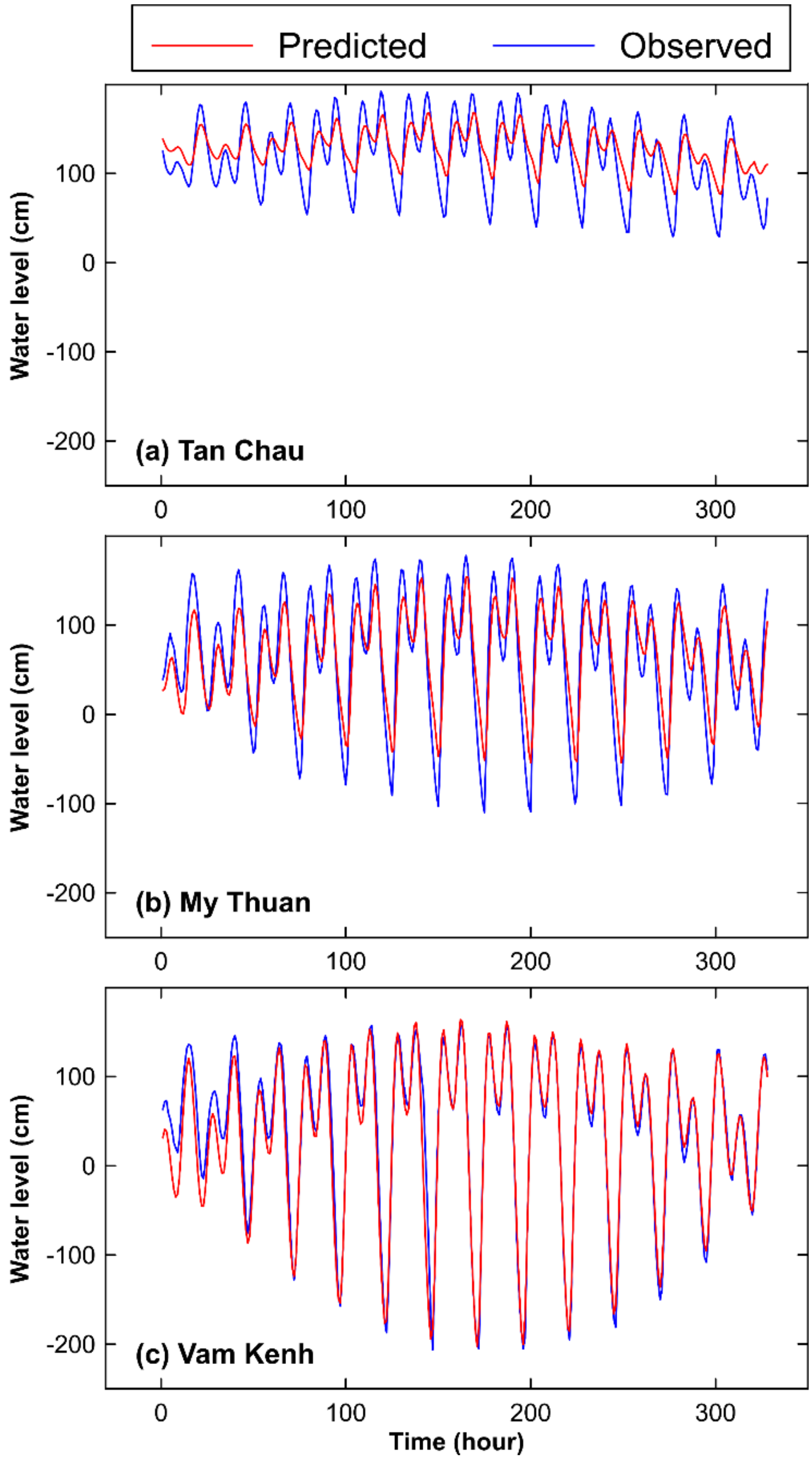

Figure 6: Time-series plot of observed and predicted water levels derived from stationary harmonic analysis.

At the My Thuan station, the LSTM model's superiority is clear at a 24-hour forecast horizon (FIGURE 7). The LSTM predictions (FIGURE 7b) match the observed data far better than the harmonic analysis results (FIGURE 7a). Harmonic analysis consistently underestimated the amplitude of water level variations (FIGURE 7c), but the LSTM model captured these fluctuations accurately. Both methods predicted the timing of tides reasonably well, but only the LSTM model provided reliable magnitudes. This demonstrates that for locations with strong fluvial-tidal interactions, deep learning models are more effective forecasting tools, a finding consistent with other case studies using similar architectures [34, 35].

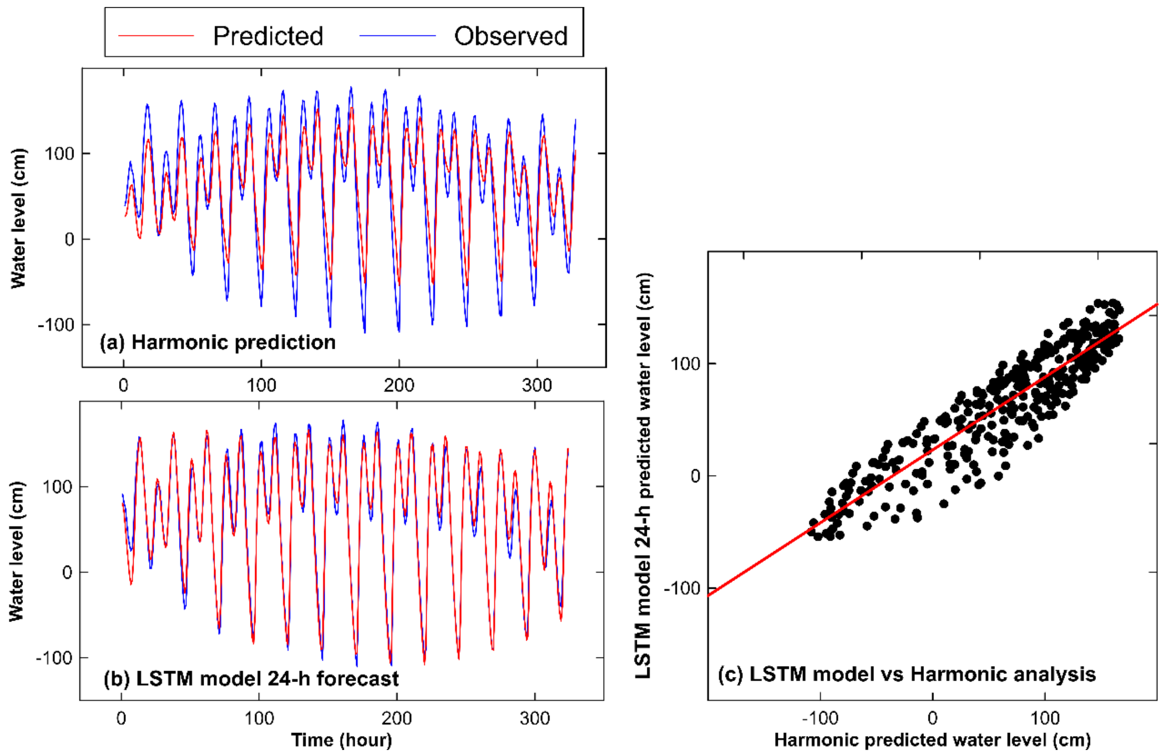

Figure 7: Time-series plot of observation and prediction water levels using harmonic analysis (a) and LSTM model (b) and for My Thuan station and comparison of predicted values between these methods (c).

4. CONCLUSION

We benchmarked a univariate LSTM model for hourly water level prediction at the My Thuan station in the Vietnamese Mekong Delta. Our results show that, using only past water level data, the LSTM model is highly effective for short-term forecasts (up to 96 hours). It performed significantly better than traditional harmonic analysis because it could capture the non-linear dynamics of the tidal system.A key finding of this work is the quantification of the model's performance decline at longer forecast horizons. We documented the operational limits of this standard univariate approach. The model's accuracy decreased because historical water levels alone are insufficient for predicting the effects of upstream discharge and other external factors that dominate over longer time scales. Our work confirms that LSTM is a useful tool for short- to medium-term operational hydrology and provides a performance baseline for future studies. We recommend that future research focus on multivariate models that include external predictors like upstream discharge, rainfall, and coastal tidal signals. Such models are needed to achieve reliable long-term forecasts. A comparative analysis against other machine learning models (e.g., SVR, Random Forest) would also be beneficial. In summary, this study defines the strengths and limits of a standard LSTM model in a complex delta. While deep learning is a powerful tool, integrating physical drivers is necessary to build the next generation of reliable, long-range water level forecasting systems.

5. ACKNOWLEDGEMENT

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References

[1] GSO. Statistical Yearbook of Vietnam 2021. General Statistics Office of Vietnam. 2021.

[2] Balica S, Dinh Q, Popescu I, Vo TQ, Pham DQ. Flood Impact in the Mekong Delta, Vietnam. J Maps. 2014;10:257-268.

[3] Tran DD, Quang CN, Tien PD, Tran PG, Kim Long P, et al. Livelihood Vulnerability and Adaptation Capacity of Rice Farmers Under Climate Change and Environmental Pressure on the Vietnam Mekong Delta Floodplains. Water. 2020;12:3282.

[4] Chen X, Liu H, Baiyinbaoligao , Mu X. Summary of Flood and Drought in Mekong River Basin. In: Liu H, editor. Flood prevention and drought relief in mékong river basin. Singapore: Springer. 2020:27-54.

[5] https://www.researchgate.net/profile/Tuan-Le-72/publication/305377337_Flood_and_salinity_management_in_the_Mekong_Delta_Vietnam/links/5865262f08ae6eb871adb22e/Flood-and-salinity-management-in-the-Mekong-Delta-Vietnam.pdf

[6] Nguyen NA. Historic Drought and Salinity Intrusion in the Mekong Delta in 2016: Lessons Learned and Response Solutions. Viet J Sci Technol Eng. 2017;59:93-96.

[7] Minh HV, Lavane K, Ty TV, Downes NK, Hong TT, Kumar P. Evaluation of the Impact of Drought and Saline Water Intrusion on Rice Yields in the Mekong Delta, Vietnam. Water. 2022;14:3499.

[8] Hoang LP, Lauri H, Kummu M, Koponen J, Van Vliet MT, Supit I, et al. Mekong River Flow and Hydrological Extremes Under Climate Change. Hydrol Earth Syst Sci. 2016;20:3027-3041.

[9] Benfer NP, King BA, Lemckert CJ. Salinity Observations in a Subtropical Estuarine System on the Gold Coast, Australia. J Coast Res. 2007;50:646-651.

[10] Arnold JG, Srinivasan R, Muttiah RS, Williams JR. Large Area Hydrologic Modeling and Assessment Part I: Model Development. J American Water Resour Assoc. 1998;34:73-89.

[11] Wang D, Wei S, Luo H, Yue C, Grunder O. A Novel Hybrid Model for Air Quality Index Forecasting Based on Two-Phase Decomposition Technique and Modified Extreme Learning Machine. Sci Total Environ. 2017;580:719-733.

[12] Granata F, Di Nunno F. Neuroforecasting of Daily Streamflows in the UK for Short- And Medium-Term Horizons: A Novel Insight. J Hydrol. 2023;624:129888.

[13] Hoitink AJ, Jay DA. Tidal River Dynamics: Implications for Deltas. Rev Geophys. 2016;54:240-272.

[14] Falahat S, Nycander J. On the Generation of Bottom-Trapped Internal Tides. J Phys Oceanogr. 2015;45:526-45.

[15] Mosavi A, Ozturk P, Chau KW. Flood Prediction Using Machine Learning Models: Literature Review. Water. 2018;10(11):1536

[16] Yaseen ZM, El-Shafie A, Jaafar O, Afan HA, Sayl KN. Artificial Intelligence-Based Models for Stream-Flow Forecasting: 2000-2015. J Hydrol. 2015;530:829-44.

[17] Phan TT, Nguyen XH. Combining Statistical Machine Learning Models With Arima for Water Level Forecasting: The Case of the Red River. Adv Water Resour. 2020;142:103656.

[18] Shen C. A Transdisciplinary Review of Deep Learning Research and Its Relevance for Water Resources Scientists. Water Resour Res. 2018;54:8558-8593.

[19] Imran M, Sheikh AK. Forecasting Water Level of Jhelum River of Kashmir Valley India, Using Prediction and Earlywarning System. Geogr Environ Sustain. 2020;13:35-42.

[20] Hochreiter S, Schmidhuber J. Long Short-Term Memory. Neural Comput. 1997;9(8):1735-1780.

[21] Kratzert F, Klotz D, Brenner C, Schulz K, Herrnegger M. Rainfall-Runoff Modelling Using Long Short-Term Memory (LSTM) Networks. Hydrol Earth Syst Sci. 2018;22:6005-6022.

[22] Atashi V, Gorji HT, Shahabi SM, Kardan R, Lim YH. Water Level Forecasting Using Deep Learning Time-Series Analysis: A Case Study of Red River of the North. Water. 2022;14:1971.

[23] Tucci M. Hourly Water Level Forecasting in an Hydroelectric Basin Using Spatial Interpolation and Artificial Intelligence. Sensors. 2022;23:203.

[24] Deng B, Liu P, Chin RJ, Kumar P, Jiang C, Xiang Y, et al. Hybrid Metaheuristic Machine Learning Approach for Water Level Prediction: A Case Study in Dongting Lake. Front Earth Sci. 2022;10:928052.

[25] Le XH, Van LN, Nguyen GV, Nguyen DH, Jung S, Lee G. Towards an Efficient Streamflow Forecasting Method for Event-Scales in Ca River Basin, Vietnam. J Hydrol Reg Stud. 2023;46:101328.

[26] Anh NT, Dat NQ, Van NT, Doanh NN, Le An N. Wavelet-Artificial Neural Network Model for Water Level Forecasting. In: 2018 International Conference on Research in Intelligent and Computing in Engineering (RICE). IEEE. 2018:1-6.

[27] Nguyen DH, Nguyen TG, Le XH, Tran NV, Huu DN. Multi-Step-Ahead Prediction of Water Levels Using Machine Learning: A Comparative Analysis in the Vietnamese Mekong Delta. J Hydrol. 2024;629:130635.

[28] Nguyen HD, Van CP, Nguyen QH, Bui QT. Daily Streamflow Prediction Based on the Long Short-Term Memory Algorithm: A Case Study in the Vietnamese Mekong Delta. J Water Clim Change. 2023;14:1247-1267.

[29] https://apps.dtic.mil/sti/html/tr/AD0831165/

[30] Minderhoud PS, Coumou L, Erkens G, Middelkoop H, Stouthamer E. Mekong Delta Much Lower Than Previously Assumed in Sea-Level Rise Impact Assessments. Nat Commun. 2019;10:3847.

[31] https://www.researchgate.net/profile/Daniel-Codiga/publication/280722790_Unified_tidal_analysis_and_prediction_using_the_UTide_Matlab_functions/links/55ff3e5808aeba1d9f8404fb/Unified-tidal-analysis-and-prediction-using-the-UTide-Matlab-functions.pdf

[32] Sahoo BB, Jha R, Singh A, Kumar D. Long Short-Term Memory (LSTM) Recurrent Neural Network for Low-Flow Hydrological Time Series Forecasting. Acta Geophys. 2019;67:1471-1481.

[33] Luo X, Zhang W, Chen S, Feng X, Ji X, et al. Evolution of Reversal of the Lowest Low Waters in a Tidal River Network. J Hydrol. 2020;585:124701.

[34] Li F, Ma G, Chen S, Huang W. An Ensemble Modeling Approach to Forecast Daily Reservoir Inflow Using Bidirectional Long- And Short-Term Memory (Bi-LSTM), Variational Mode Decomposition (VMD), and Energy Entropy Method. Water Resour Manag. 2021;35:2941-2963.

[35] Hieu TT, Chieu TQ, Quang DN, Hieu ND. Water Level Prediction Using Deep Learning Models: A Case Study of the Kien Giang River, Quang Binh Province. River. 2023;2:468-479.