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Tidal level forecasting: a comparative study of random forest and long short-term memory networks

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ABSTRACT

Increasing coastal risks necessitate reliable tidal forecasts for coastal planning and disaster risk reduction. This study evaluates random forest (RF) and long short-term memory (LSTM) models for next-day, daily-averaged tidal-level forecasting, utilizing five years (2020–2024) of multivariate environmental data (humidity, rainfall, solar radiation, wind speed, and tidal series) from South Kalimantan, Indonesia. Missing data were linearly interpolated, and tidal extremes prone to leakage were excluded. RF incorporated 35 flattened seven-day lag features, while LSTM employed normalized seven-day sliding-window sequences. On the withheld 2024 test set, LSTM demonstrated lower root mean square error (RMSE) and higher coefficient of determination (R^2)/Nash–Sutcliffe efficiency (NSE) than RF (RMSE 0.200 vs 0.208; R^2/NSE 0.181 vs 0.118), whereas RF achieved a marginally lower mean absolute error (MAE) (0.124 vs 0.126). A paired Wilcoxon test indicated a modest but statistically significant LSTM advantage ($p = 0.049$), not supported by a paired t-test ($p = 0.663$). Both models exhibited limited explanatory power and missed the most volatile periods. RF feature importance analysis revealed that short-term persistence in the tidal series, rather than individual covariates, primarily influenced performance. Supported by bootstrap confidence and prediction intervals, these results offer a regional case study for environmentally informed tidal forecasting in data-constrained Indonesian coastal environments.

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1. INTRODUCTION

Coastal regions are dynamic environments influenced by both natural oceanographic processes and human activities. Accurate tidal level forecasting is essential for navigation safety, marine infrastructure planning, aquaculture, and disaster risk reduction. This need is particularly pronounced in Indonesia, an archipelagic nation where a significant portion of the coastal population is directly exposed to tidal variation [1], [2]. In South Kalimantan, the focus of this study, dense coastal settlements coincide with limited long-term, multivariate monitoring infrastructure.

Traditional tidal prediction methods rely on harmonic analysis of astronomical constituents, which do not directly account for meteorological and hydrological drivers such as rainfall, wind, solar heating, and

humidity. The expansion of in-situ sensor networks and internet of things (IoT) platforms has enabled continuous, multivariate coastal monitoring [3]–[5], generating high-resolution records suitable for modeling atmosphere–ocean interactions [6]. However, utilizing these data for predictive modeling remains challenging due to temporal dependencies and nonlinear interactions among environmental variables [7]. Additionally, operational sensor networks are often less comprehensive than the datasets typically used to benchmark deep learning (DL) methods.

Machine learning (ML) and DL methods are increasingly applied to tidal and coastal water-level forecasting. Sequence-learning models such as long short-term memory (LSTM) and gated recurrent unit (GRU) networks have demonstrated improved accuracy over classical baselines for sea-level and tidal-level prediction [1], [2], [8], [9]. Another research direction develops hybrid, physically informed pipelines. For example, theory-guided architectures that combine harmonic analysis with LSTM, bidirectional long short-term memory (BiLSTM), and GRU have enhanced tidal prediction when meteorological covariates such as wind are included [10]. Ensemble empirical mode decomposition (EEMD) has been used to separate nonlinear tidal fluctuations from typhoon-driven noise before forecasting [11], and hybrid feature-selection frameworks have improved tidal power forecasting by removing irrelevant predictors [12]. These hybrid approaches often require additional inputs, such as harmonic constituents, extensive decomposition preprocessing, or hydrodynamic simulation outputs, which are not always operationally available. Furthermore, several of these methods have been validated primarily on synthetic data or short, single-point records rather than on multi-year, multi-sensor, real-world datasets like those analyzed in this study [13]–[15]. In contrast, tree-based ensembles such as random forest (RF) have proven effective for related tasks, including surface-water salinity estimation [16] and time-lag-informed streamflow prediction [17], by leveraging lagged predictors without the need for sequential input structures. However, RF has not been systematically benchmarked against LSTM for multivariate, sensor-based tidal forecasting in the Indonesian coastal context.

The existing literature reveals two primary gaps. First, there is a lack of comparative evaluations that directly contrast tabular, lag-based ML approaches with sequence-based DL approaches using the same real-world, multi-year, multivariate sensor datasets, rather than relying on synthetic data or simulation outputs [13]–[15]. Additionally, the systematic tailoring of input representations—specifically, flattened lag features for RF and sliding-window sequences for LSTM—has not been thoroughly investigated in the context of tidal forecasting. Second, prior studies do not address the generalizability of their findings to other coastal regions, extended forecasting horizons, or the extreme tidal events most relevant for disaster risk reduction. Consequently, the present study is structured as a single-region, next-day, daily-averaged case study, with this scope explicitly defined as a boundary condition (see section 3, limitations).

To address these gaps, this study compares RF and LSTM models for next-day tidal-level forecasting using five years (2020–2024) of real, multivariate environmental sensor data from South Kalimantan. The input variables include humidity, rainfall, solar radiation, wind speed, and the tidal series. RF effectively captures nonlinear interactions with minimal preprocessing [18], while LSTM models learn sequential dependencies directly from time-series data [8], [9]. This research makes four key contributions: i) a controlled, same-data, same-split comparison between a tabular ML method RF and a sequence-based DL method LSTM using operational sensor data rather than synthetic records; ii) consistent application of model-specific feature engineering (flattened lag features for RF and sliding-window sequences for LSTM) to isolate the effect of input representation; iii) an empirical case study based on South Kalimantan's coastal conditions, which have not previously been used for this comparison, thereby extending the geographic evidence base for environmentally aware tidal forecasting in Indonesia; and iv) an uncertainty-quantified evaluation, including confidence intervals, prediction intervals, and a paired significance test (see section 2.6), alongside point-estimate accuracy [19], to provide a more decision-relevant foundation for operational coastal monitoring and disaster risk reduction.

2. METHOD

This study employs a six-stage framework: dataset description, data preprocessing, feature engineering, data scaling, modelling, and evaluation. The framework is adapted for RF, which utilizes flattened lag features, and LSTM, which utilizes normalized sliding-window sequences. The underlying data, target definition, and train/test split remain consistent across both models.

2.1. Data source

Tidal-level data were sourced from the Indonesian Navy's Hydro-Oceanographic Centre (Pushidrosal) for South Kalimantan, including daily minimum, maximum, and mean tidal heights from January 2020 to December 2024. Additional daily measurements of humidity, rainfall, solar radiation, and

wind speed were obtained from BMKG and temporally aligned with the tidal records. These four variables were retained due to their established relevance to coastal and atmosphere–ocean processes, although, as demonstrated in section 3, their individual explanatory power was less significant than the short-term persistence observed in the tidal series.

The consolidated five-year dataset covers 1,827 calendar days, with 1,704 days represented in the raw source files. Two dates (14 and 19 November 2020) appeared as duplicates with differing values; in each case, the first-recorded entry was retained. The remaining 123 days were missing entirely, distributed across 103 short gap segments (83 single-day, 18 two-day, and 2 three-day gaps), a pattern characteristic of intermittent reporting in in-situ coastal sensor networks [3], [4] rather than prolonged instrument failure. For models trained on seven-day windows, these short, scattered gaps can be addressed through linear interpolation with minimal risk, in contrast to the challenges posed by longer data outages.

Following chronological windowing and reserving 2024 data for testing, the training set consists of approximately 1,450 seven-day sequences, which is relatively small by DL standards. Consequently, the LSTM results presented in section 3 should be interpreted as evidence of feasibility for data-constrained, single-region records, rather than as an indication of the model's asymptotic capacity. Further discussion is provided in section 3.

2.2. Data preprocessing

The tidal and environmental datasets were merged based on date. Missing values, including both originally absent readings and the 123 calendar days identified in section 2.1 as lacking corresponding rows, were addressed by reindexing to a complete daily calendar for 2020 to 2024 and applying linear interpolation across all numeric columns. As every identified gap was three days or shorter, linear interpolation represents an appropriate and low-risk method for this dataset [18]. A feature-reduction step removed the minimum and maximum tidal columns, as both are closely related to the mean tidal level used as the target and would introduce leakage that could overstate model performance [20]. Only the mean tidal level ("pasang_rata") was retained as the target variable, together with the four environmental predictors, and the dataset was sorted chronologically for subsequent feature engineering (subsection 2.3).

2.3. Feature engineering

Both models predict the mean tidal level on day t using data from the preceding seven days (t−7 to t−1), thereby standardizing the target definition and forecast horizon while differing solely in input representation. For the RF model, the seven-day history of all five variables (humidity, rainfall, solar radiation, wind speed, and tidal level) was transformed into 35 lag features (kelembapan_lag1…kelembapan_lag7, …, pasang_rata_lag1…pasang_rata_lag7). This approach provides RF with explicit access to the recent history of the tidal series and associated environmental covariates. In contrast, for the LSTM model, the same seven-day history was structured as a three-dimensional sequence (7 timesteps × 5 features), thereby preserving the temporal ordering that is lost in the RF's flattened representation. Table 1 summarizes these differences.

Table 1. Summary of feature engineering differences

Aspect	RF	LSTM
Input features	35 flattened lag features: 5 variables × 7 lags (incl. pasang_rata_lag1…lag7)	Sequential window, 7 timesteps × 5 features (incl. pasang_rata)
Temporal modelling	Not required (order discarded)	Required (order preserved)
Normalization	Not required	MinMaxScaler, fit on train only
Input shape	Flat vector (35,)	3D array (7, 5)
Target	pasang_rata(t)	pasang_rata(t)

2.4. Data scaling

RF predictors were implemented without normalization, reflecting the scale-invariance of tree-based split criteria. LSTM model inputs and targets were normalized using a min-max scaler fitted solely on the training partition (2020-01-08 to 2023-12-31). This scaler was then applied unchanged to the 2024 test partition, ensuring that no information from the test period's value range influenced the scaling transformation, in accordance with recommended data-scaling practices for ML and DL models [20].

2.5. Modelling

The RF model was implemented using scikit-learn's RandomForestRegressor with 100 trees, a maximum depth of 10, and random_state set to 42. All other hyperparameters were maintained at their scikit-learn default values, as shown in Table 2. A comprehensive grid search was not performed; the

selection of 100 trees is consistent with ranges commonly reported as sufficient for error stabilization in tabular tree-ensemble regression at this sample size [17], [21]. Limiting the maximum depth to 10 was intended to prevent overfitting in the approximately 1,450-sample, 35-dimensional training set, thereby prioritizing improved generalization to 2024 over marginal gains in training-set fit. A systematic sensitivity analysis is proposed as future work (section 4), as it falls outside the present study's focus on RF versus LSTM models.

Table 2. Hyperparameters configuration for RF

Parameter	Value
n_estimators	100
max_depth	10
random_state	42
Other parameters	Scikit-learn defaults

The LSTM model was implemented in Keras with a single recurrent layer of 64 units [22], followed by a dense (1) output layer. Training was conducted using the Adam optimizer (learning rate = 0.001) for 50 fixed epochs with a batch size of 32, without dropout or early stopping, to maintain model capacity appropriate for the modest training set size. In practice, 50 epochs were sufficient for the training loss to plateau. The LSTM configuration is presented in Table 3. This approach differs from early-stopping-based regularization, which has been shown to improve convolutional neural network (CNN)-LSTM classification performance in other studies [23].

Table 3. LSTM model configuration

Parameter	Value
LSTM layer	1 layer, 64 units
Output layer	Dense(1)
Optimizer	Adam (lr = 0.001)
Loss function	MSE
Epochs	50 (fixed, no early stopping)
Batch size	32

2.6. Model evaluation

Model performance was evaluated using mean absolute error (MAE), root mean square error (RMSE), coefficient of determination (R^2) [19], and Nash–Sutcliffe efficiency (NSE) [24]. In this study, the R^2 formulation and the NSE are both defined as 1 minus the ratio of the residual sum of squares to the total sum of squares about the observed mean, yielding numerically identical values. NSE is reported alongside R^2 to maintain consistency with hydrological forecasting conventions, rather than as an independent metric.

95% confidence intervals for MAE, RMSE, and R^2/NSE were estimated using nonparametric bootstrap resampling [25] of the paired actual and predicted test-set observations. This procedure involved 5,000 resamples with replacement and the percentile method, computed directly from the 2024 test-set residuals without additional model training. Empirical prediction intervals at the 90% and 95% levels for individual next-day forecasts were similarly derived from each model's test-set residual quantiles. The statistical significance of the difference between RF and LSTM models was assessed using paired, same-date absolute test-set errors. Both a paired Wilcoxon signed-rank test and a paired t-test were applied [26], as the two models were evaluated on the same 366 test dates and thus do not represent independent samples.

3. RESULTS AND DISCUSSION

The performance of both models was evaluated using the withheld 2024 test year, comprising 366 days. Table 4 presents MAE, RMSE, and R^2/NSE for each model. It also includes the corresponding 95% bootstrap confidence intervals.

Table 4. Model evaluation results on the 2024 test set

Model	MAE	RMSE	R^2
RF	0.124 (0.108–0.142)	0.208 (0.177–0.239)	0.118 (0.038–0.194)
LSTM	0.126 (0.110–0.142)	0.200 (0.172–0.228)	0.181 (0.092–0.260)

LSTM achieves a lower RMSE and higher R^2/NSE compared to RF, while RF achieves a marginally lower MAE. The RMSE and R^2/NSE intervals overlap only partially, whereas the MAE intervals overlap almost entirely. Both models demonstrate modest, statistically significant but practically limited explanatory power, which is characteristic of daily-averaged tidal forecasting based on environmental covariates rather than harmonic constituents and is comparable to other complex environmental forecasting tasks [27], [28]. Therefore, neither model should be interpreted as providing high-precision absolute-level forecasts.

The results of the paired significance tests are mixed. The Wilcoxon signed-rank test on paired absolute errors favors LSTM (p = 0.049), whereas the paired t-test on the same errors does not (p = 0.663), nor does the paired t-test on squared errors (p = 0.115). These findings indicate that LSTM produces smaller errors on most individual test days, but the margin is neither large nor consistent. Consequently, the difference between RF and LSTM should be interpreted as directionally suggestive rather than conclusive for this single 366-day test year. The 90% empirical prediction intervals were (−0.369 m, +0.281 m) for RF and (−0.327 m, +0.265 m) for LSTM, with 95% intervals of (−0.527 m, +0.396 m) and (−0.543 m, +0.415 m) respectively; LSTM's narrower 90% interval matches its lower RMSE, while the 95% widths are comparable, reflecting shared difficulty bounding the largest residuals.

Figure 1 presents a comparison between LSTM predictions and the observed mean tidal level for 2024, while Figure 2 provides the corresponding results for RF. Both models capture the general trend and gradual variations but fail to accurately represent short-term amplitude fluctuations. The observed series exhibits high volatility from January through June, becomes notably calmer from July through November, and displays a pronounced spike in mid-to-late December. Neither model successfully anticipates these short-term variations, particularly during the volatile January to June period and the December anomaly. Figure 3 illustrates that both residual distributions are unimodal and centered near zero. Figure 3(a) shows the residual distribution for RF, while Figure 3(b) shows the residual distribution for LSTM. Heavy tails beyond ±0.5 m correspond to previously identified volatile and anomalous periods. The LSTM distribution is slightly more concentrated near zero, which aligns with its lower RMSE.

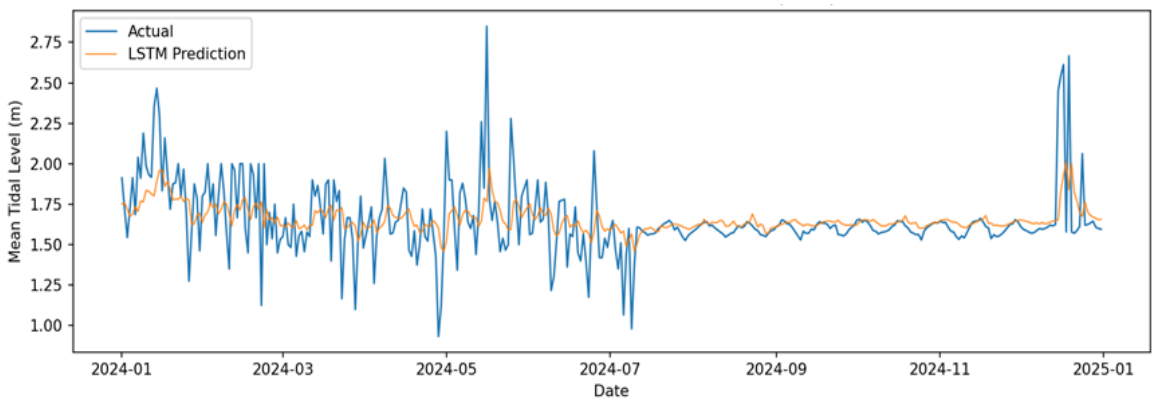

Figure 1. LSTM: predicted vs actual mean tidal level (2024 test set)

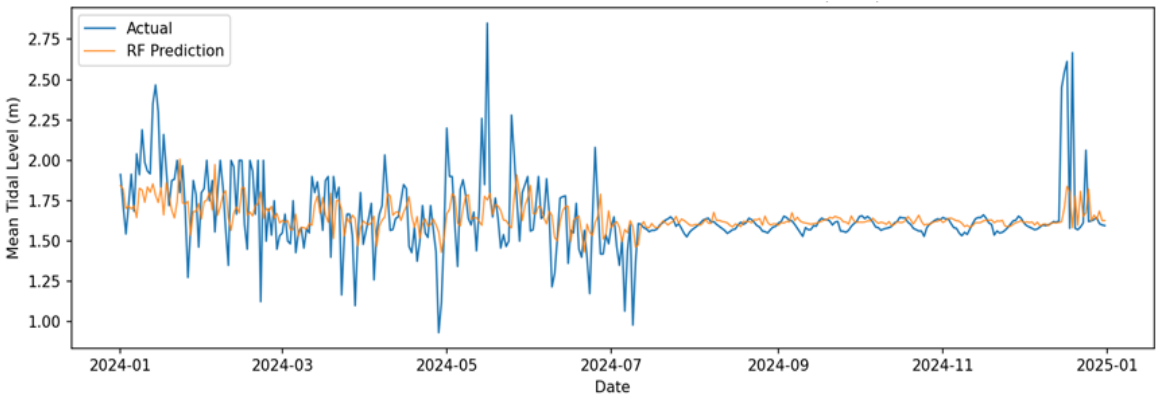

Figure 2. RF: predicted vs actual mean tidal level (2024 test set)

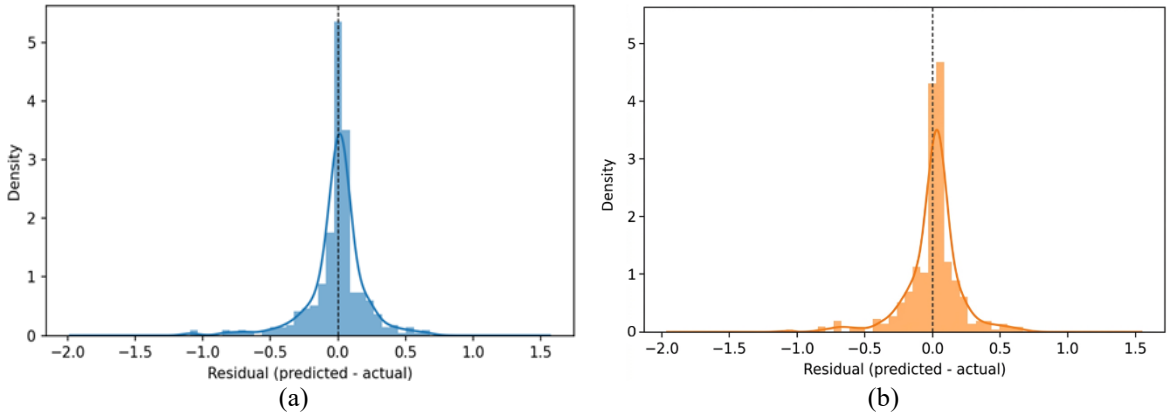

Figure 3. Residual distribution for (a) RF and (b) LSTM

Figure 4 displays the feature importances for the RF model. The one-day tidal lag (pasang_rata_lag1, importance ≈ 0.21) emerges as the most influential feature, followed by the two- and three-day tidal lags (≈ 0.08 and ≈ 0.06, respectively). The four environmental variables demonstrate lower and more distributed importance across their seven lags, with none exceedingly approximately 0.03. Therefore, the majority of the RF model's predictive capability can be attributed to the short-term persistence of the tidal series rather than to the environmental covariates.

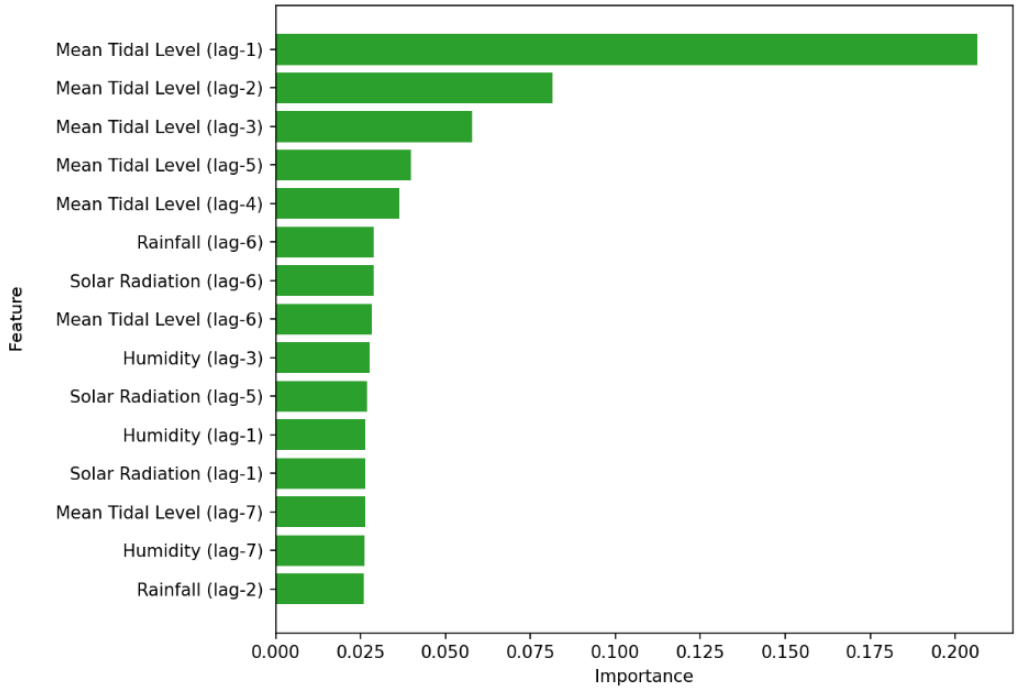

Figure 4. RF: top 15 feature importances

3.1. Why long short-term memory outperforms random forest

The results, with LSTM outperforming on RMSE and R^2/NSE, RF marginally ahead on MAE, and statistical significance directionally but not conclusively favoring LSTM, require a mechanistic explanation. The RF model's flattened 35-feature representation treats each lagged value as an independent split criterion [21], thereby discarding sequential ordering, a limitation identified in other RF forecasting applications [29]. In contrast, LSTM's recurrent gating structure [22] processes the seven-day window as an ordered sequence, learning a time-dependent weighting of the autoregressive and environmental signals

jointly. This structuring has been shown to improve the capture of spatiotemporal dependencies in other contexts [30]. This likely enables LSTM to avoid some of the largest residuals, resulting in lower RMSE, which penalizes large errors quadratically, even though its typical error is similar to RF's, as indicated by the near-identical MAE. A similar pattern is observed in the theory-guided harmonic-LSTM/BiLSTM/GRU study on the Taehwa River, where recurrent architectures improved performance once meteorological covariates were incorporated jointly with the tidal signal, as well as in LSTM-based tidal- and sea-level forecasting studies more broadly. Comparable RMSE and R^2 gaps without a corresponding MAE gap have also been reported between tree-ensemble and sequence models on related environmental forecasting problems [31], [32]. In harmful-algal-bloom forecasting, sequence models exploited spatiotemporal correlation more effectively than flattened lag representations once an autoregressive signal was present [33], which is analogous to the pasang_rata_lag1 dominance observed in Figure 4.

The feature-importance ranking from RF provides a complementary explanation. With approximately one-fifth of its total importance assigned to pasang_rata_lag1, RF operates similarly to a regularized autoregressive model with secondary environmental adjustments, whereas LSTM integrates both signals more flexibly across the input window. Caution is warranted, however, because RF variable-importance measures are known to be biased toward mutually correlated predictors [34]. The 35 lag features include several correlated adjacent-day lags of the same variable, so the concentration on pasang_rata_lag1 may partly reflect this correlation rather than a purely independent contribution. The conditional importance procedure could help disentangle this effect [34]. Nevertheless, the ranking aligns with the tidal series' modest one-day autocorrelation and the near-zero same-day correlation of the environmental variables individually. This helps explain why neither model achieves strong absolute accuracy. Further improvements are more likely to result from better exploitation of temporal structure, as LSTM does to a modest extent, rather than from the environmental variables themselves. This is consistent with findings that feature engineering alone is often insufficient in other RF-based prediction tasks [35].

3.2. Limitations

The scope of this study is restricted to a single coastal region (South Kalimantan) and a five-year dataset. Consequently, the reported accuracy, feature-importance patterns, and RF–LSTM comparison may not generalize to other coastal regions without additional validation, which is identified as a direction for future research. The forecasting horizon assessed is limited to next-day, daily-averaged tidal levels; performance at longer horizons or sub-daily resolution was not evaluated. The training set, following windowing, consists of approximately 1,450 sequences spanning four years, which is modest by deep learning standards and may constrain the LSTM's capacity to generalize beyond the specific inter-annual variability observed in 2020–2023, as reflected in the wide confidence intervals in Table 4. The sensor record was incomplete: 123 out of 1,827 calendar days lacked source data and were filled by linear interpolation (subsection 2.1–2.2). Although all gaps were brief (≤ 3 days), data quality was not entirely uniform throughout the record. Both models under-tracked the largest deviations in the test year, particularly during the volatile January–June 2024 period and the December 2024 anomaly (Figures 1 to 3). This suggests that the framework is more effective for typical near-term tidal behavior than for predicting extreme or anomalous events, which are critical for disaster risk reduction. Several analyses were intentionally excluded from the controlled RF-versus-LSTM scope of this study. Benchmarking against GRU and hybrid CNN-LSTM architectures, as well as conducting an ablation study to isolate lag features from sequential windows, would expand the experimental scope and are proposed as direct extensions using the same dataset and protocol. Additionally, a systematic hyperparameter sensitivity analysis, including a comparison of fixed-epoch training with early-stopping-based regularization for LSTM [23], was replaced with qualitative justification and is recommended as a more rigorous follow-up. Finally, hybrid RF–LSTM ensemble architectures, which have demonstrated improved daily-resolution forecasting in other domains [36], were not examined.

3.3. Hypothetical deployment scenario

Despite these limitations, the framework could feasibly support a decision-support layer for South Kalimantan's coastal authorities. A daily BMKG feed, combined with the trained RF and/or LSTM models, could generate a next-day tidal nowcast with prediction intervals as described in section 3. This system would flag days when the forecast interval deviates significantly from typical conditions, thereby alerting fisheries, small-craft navigation, or disaster-preparedness personnel. Such a tool would supplement, rather than replace, conventional harmonic tide tables, given the current accuracy of the models. The present study did not benchmark the framework against conventional harmonic tidal analysis, as harmonic methods require tidal-constituent data that differ fundamentally from the environmental sensor inputs used in this research. Therefore, this comparison is proposed as future work rather than considered a limitation of the current analysis. Any operational deployment of these models should include clear communication of

forecast uncertainty and a defined fallback to conventional tide tables during periods of missing or delayed sensor data, given the region's dependence on tidal information for fisheries and small-craft navigation safety.

4. CONCLUSION

This study compares RF and LSTM models for next-day, daily-averaged tidal-level forecasting using five years (2020–2024) of real multivariate sensor data from South Kalimantan, evaluated on a withheld 2024 test year. The LSTM model achieved a lower RMSE and higher R^2 and NSE than the RF model (RMSE 0.200 vs 0.208; R^2/NSE 0.181 vs 0.118), while RF obtained a marginally lower MAE (0.124 vs 0.126). A paired Wilcoxon test indicated a modest but statistically significant advantage for LSTM ($p = 0.049$), whereas a paired t-test did not corroborate this finding ($p = 0.663$). The primary contribution is a controlled, same-data comparison of a tabular ML approach and a sequence-based DL approach on real, multi-year sensor data from an Indonesian coastal region not previously examined for this comparison, with uncertainty quantified through bootstrap confidence and prediction intervals. RF feature importance analysis indicated that the predictive signal is derived mainly from the short-term persistence of the tidal series rather than from individual environmental covariates. These findings represent a regional case study and do not constitute a general claim regarding RF versus LSTM performance across coastal regions. Future research should incorporate GRU and hybrid CNN-LSTM benchmarks, hyperparameter sensitivity analysis, additional predictors such as lunar phase and atmospheric pressure, cross-regional and longer-horizon testing, hybrid RF–LSTM ensembles, and real-time IoT integration for operational coastal monitoring and early warning.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study were obtained from the first author. These data were used with permission and are not publicly available due to licensing restrictions. Access requests may be directed to the corresponding author, [D], subject to approval from the original authors.

REFERENCES

[1] A. Y. Winona and D. Adytia, "Short term forecasting of sea level by using LSTM with limited historical data," in *2020 International Conference on Data Science and Its Applications,* 2020, pp. 1–4, doi: 10.1109/ICoDSA50139.2020.9213025.

[2] A. P. Sari and D. Adytia, "Sea level time series forecasting by using LSTM with attention mechanism, a case study in Jakarta, Indonesia," in *2024 International Conference on Data Science and Its Applications, ICoDSA 2024*, 2024, pp. 328–333, doi: 10.1109/ICoDSA62899.2024.10652146.

[3] M. R. Routhier, B. R. Curran, C. H. Carlson, and T. A. Goddard, "Remote sensing and assessment of compound groundwater flooding using an end-to-end wireless environmental sensor network and data model at a coastal cultural heritage site in Portsmouth, NH," *Sensors*, vol. 24, no. 20, 2024, doi: 10.3390/s24206591.

[4] T. L. Narayana *et al.*, "Advances in real-time smart monitoring of environmental parameters using IoT and sensors," *Heliyon*, vol. 10, no. 7, 2024, doi: 10.1016/j.heliyon.2024.e28195.

[5] S. Ginanjar, S. Adiningsih, Y. N. Fadlilah, S. Wulandari, C. B. Petrova, and S. Ikhtiarino, "Coastal storm waves detection system design using Beaufort scale standardization and Sugianto wave forecasting method in Timbulsloko, Demak, Central Java, Indonesia," in *2nd International Conference on Tropical Meteorology and Atmospheric Sciences*, 2021, doi: 10.1088/1755-1315/893/1/012066.

[6] A. Patrignani, M. Knapp, C. Redmond, and E. Santos, "Technical overview of the Kansas Mesonet," *Journal of Atmospheric and Oceanic Technology*, vol. 37, no. 12, pp. 2167–2183, 2020, doi: 10.1175/JTECH-D-19-0214.1.

[7] Q. Zhou *et al.*, "Short-term prediction of vertical deformation in tidal flat terrains based on PSO-VMD-LSTM," *IEEE Transactions on Instrumentation and Measurement*, vol. 73, pp. 1–14, 2024, doi: 10.1109/TIM.2024.3413180.

[8] C. H. Yang, C. H. Wu, and C. M. Hsieh, "Long short-term memory recurrent neural network for tidal level forecasting," *IEEE Access*, vol. 8, pp. 159389–159401, 2020, doi: 10.1109/ACCESS.2020.3017089.

[9] A. W. Ramadhan, D. Adytia, D. Saepudin, S. Husrin, and A. Adiwijaya, "Forecasting of sea level time series using RNN and LSTM case study in sunda strait," *Lontar Komputer : Jurnal Ilmiah Teknologi Informasi*, vol. 12, no. 3, pp. 130–140, 2021, doi: 10.24843/lkjiti.2021.v12.i03.p01.

[10] K. Y. Kareem, Y. Seong, K. Kim, and Y. Jung, "A case study of tidal analysis using theory-based artificial intelligence techniques for disaster management in Taehwa River, South Korea," *Water*, vol. 14, no. 14, 2022, doi: 10.3390/w14142172.

[11] Y. C. Chen, H. C. Yeh, S. P. Kao, C. Wei, and P. Y. Su, "Water level forecasting in tidal rivers during typhoon periods through ensemble empirical mode decomposition," *Hydrology*, vol. 10, no. 2, 2023, doi: 10.3390/hydrology10020047.

[12] H. H. Aly, "A proposed hybrid machine learning model based on feature selection technique for tidal power forecasting and its integration," *Electronics*, vol. 13, no. 11, 2024, doi: 10.3390/electronics13112155.

[13] G. Tong, J. Chao, W. Ma, Z. Zhong, G. Gupta, and W. Zhu, "Leveraging synthetic data to improve regional sea level predictions," *Scientific Reports*, vol. 15, no. 1, pp. 1–10, 2025, doi: 10.1038/s41598-025-88078-1.

[14] Z. Zhu, X. Yan, Z. Wang, and S. Liu, "Spatiotemporal prediction of tidal fields in a semi-enclosed marine bay using deep learning," *Water*, vol. 17, no. 3, pp. 1–20, 2025, doi: 10.3390/w17030386.

[15] S. Huang, H. Nie, J. Jiao, H. Chen, and Z. Xie, "Tidal level prediction model based on VMD-LSTM neural network," *Water*, vol. 16, no. 17, 2024, doi: 10.3390/w16172452.

[16] R. Borovskaya, D. Krivoguz, S. Chernyi, E. Kozhurin, V. Khorosheltseva, and E. Zinchenko, "Surface water salinity evaluation and identification for using remote sensing data and machine learning approach," *Journal of Marine Science and Engineering*, vol. 10, no. 2, 2022, doi: 10.3390/jmse10020257.

[17] D. M. Moges *et al.*, "Streamflow prediction with time-lag-informed random forest and its performance compared to SWAT in diverse catchments," *Water*, vol. 16, no. 19, 2024, doi: 10.3390/w16192805.

[18] J. Alessandri, N. Pinardi, I. Federico, and A. Valentini, "Storm surge ensemble prediction system for lagoons and transitional environments," *Weather and Forecasting*, vol. 38, no. 9, pp. 1791–1806, 2023, doi: 10.1175/WAF-D-23-0040.1.

[19] D. Chicco, M. J. Warrens, and G. Jurman, "The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation," *PeerJ Computer Science*, vol. 7, pp. 1–24, 2021, doi: 10.7717/PEERJ-CS.623.

[20] P. Koukaras and C. Tjortjis, "Data preprocessing and feature engineering for data mining: techniques, tools, and best practices," *AI*, vol. 6, no. 10, 2025, doi: 10.3390/ai6100257.

[21] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, Oct. 2001, doi: 10.1023/A:1010933404324.

[22] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997, doi: 10.1162/neco.1997.9.8.1735.

[23] M. K. Anam, S. Defit, Haviluddin, L. Efrizoni, and M. B. Firdaus, "Early stopping on CNN-LSTM development to improve classification performance," *Journal of Applied Data Sciences*, vol. 5, no. 3, pp. 1175–1188, 2024, doi: 10.47738/jads.v5i3.312.

[24] J. E. Nash and J. V. Sutcliffe, "River flow forecasting through conceptual models part I - a discussion of principles," *Journal of Hydrology*, vol. 10, no. 3, pp. 282–290, 1970, doi: 10.1016/0022-1694(70)90255-6.

[25] B. Efron, "Bootstrap methods: another look at the Jackknife," *The Annals of Statistics*, vol. 7, no. 1, pp. 1280–1289, 2007, doi: 10.1214/aos/1176344552.

[26] J. Demšar, "Statistical comparisons of classifiers over multiple data sets," *Journal of Machine Learning Research*, vol. 7, pp. 1–30, 2006, doi: 10.5555/1248547.1248548.

[27] G. Wang *et al.*, "A new hybrid deep sequence model for decomposing, interpreting, and predicting sulfur dioxide decline in coastal cities of Northern China," *Sustainability*, vol. 17, no. 6, 2025, doi: 10.3390/su17062546.

[28] C. H. Cordova, M. N. L. Portocarrero, R. Salas, R. Torres, P. C. Rodrigues, and J. L. L.-Gonzales, "Air quality assessment and pollution forecasting using artificial neural networks in Metropolitan Lima-Peru," *Scientific Reports*, vol. 11, no. 1, pp. 1–19, 2021, doi: 10.1038/s41598-021-03650-9.

[29] J. Tan, "NVIDIA stock price prediction by machine learning," *Highlights in Business, Economics and Management*, vol. 24, pp. 1072–1076, 2024, doi: 10.54097/dsz8ns50.

[30] M. Yousefi *et al.*, "Short-term inflow forecasting in a dam-regulated river in Southwest Norway using causal variational mode decomposition," *Scientific Reports*, vol. 13, no. 1, pp. 1–16, 2023, doi: 10.1038/s41598-023-34133-8.

[31] B. Zhai, Y. Wang, and B. Wu, "An ensemble learning method for low visibility prediction on freeway using meteorological data," *IET Intelligent Transport Systems*, vol. 17, no. 11, pp. 2237–2250, 2023, doi: 10.1049/itr2.12404.

[32] H. Su, T. Qin, A. Wang, and W. Lu, "Reconstructing ocean heat content for revisiting global ocean warming from remote sensing perspectives," *Remote Sensing*, vol. 13, no. 19, 2021, doi: 10.3390/rs13193799.

[33] Q. Jia, C. Xu, H. Jia, C. Velazquez, L. Leng, and D. Yin, "Mining spatiotemporal information for harmful algal bloom forecasting and mechanism interpreting," *ACS ES and T Water*, vol. 4, no. 6, pp. 2608–2618, 2024, doi: 10.1021/acsestwater.4c00115.

[34] C. Strobl, A. L. Boulesteix, T. Kneib, T. Augustin, and A. Zeileis, "Conditional variable importance for random forests," *BMC Bioinformatics*, vol. 9, pp. 1–11, 2008, doi: 10.1186/1471-2105-9-307.
[35] H.-B. Ly and B. Thai Pham, "Soil unconfined compressive strength prediction using random forest (RF) machine learning model," *The Open Construction & Building Technology Journal*, vol. 14, no. 1, pp. 278–285, 2020, doi: 10.2174/1874836802014010278.
[36] J. W. Bi, C. Li, H. Xu, and H. Li, "Forecasting daily tourism demand for tourist attractions with big data: an ensemble deep learning method," *Journal of Travel Research*, vol. 61, no. 8, pp. 1719–1737, 2022, doi: 10.1177/00472875211040569.

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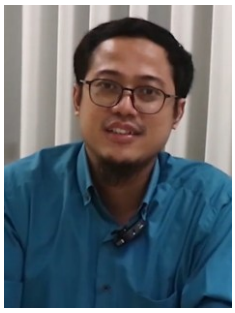

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