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Hybrid Bootstrap–LSTM Model for Probabilistic Sea Level Rise Prediction

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ABSTRACT: Sea level rise poses increasing risks to coastal regions, highlighting the need for accurate and reliable forecasting methods. This study proposes a probabilistic sea level forecasting framework by integrating a Long Short-Term Memory (LSTM) model with the Moving Block Bootstrap (MBB) technique. The LSTM model is used to capture nonlinear temporal dependencies in sea level time-series data, while the bootstrap approach is employed to quantify prediction uncertainty through probabilistic forecasting. The LSTM model achieved high deterministic prediction accuracy with an MSE of $2.11 \times 10^{!"}$, RMSE of 0.00459, MAE of 0.00356, and MAPE of 0.34%. The proposed hybrid MBB–LSTM model generates probabilistic forecasts with a 95% confidence interval, resulting in an MSE of 0.01155, RMSE of 0.10749, MAE of 0.08370, and MAPE of 8.99%. Forecast results indicate relatively stable sea level variability until 2026 with an estimated rising trend of approximately 7.44 mm per year. The proposed hybrid framework provides a more informative prediction approach by combining deep learning with bootstrap-based uncertainty estimation, which is valuable for coastal risk assessment and climate adaptation planning.

KEYWORDS: Sea level prediction, Long Short-Term Memory, Moving Block Bootstrap, Probabilistic forecasting, Time series analysis, Sea level rise.

INTRODUCTION

Climate-induced changes in ocean dynamics have increasingly affected coastal environments, particularly through sea-level rise and the occurrence of extreme tidal events [1]. Variations in atmospheric circulation, ocean temperature, and wind-driven processes contribute to more complex marine conditions, leading to higher uncertainty in coastal hydrodynamics [2]. These evolving patterns not only influence long-term sea-level trends but also intensify short-term fluctuations that may trigger coastal flooding and related hazards [3], [4]. Consequently, reliable prediction of sea-level variability has become essential for coastal risk management, maritime operations, and infrastructure planning [6].

Modeling sea-level dynamics remains challenging due to the nonlinear and nonstationary characteristics of oceanographic time-series data. Traditional statistical approaches often struggle to capture long-term temporal dependencies and complex interactions among environmental drivers. In response to these limitations, deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, have gained significant attention in environmental forecasting [5]. LSTM architectures are designed to learn sequential dependencies and nonlinear relationships, making them suitable for tidal and sea-level prediction tasks. Recent studies demonstrate that LSTM-based and hybrid deep learning models can outperform conventional approaches in representing marine temporal patterns and improving predictive accuracy [7], [8]. Hybrid models such as TCN–LSTM [9], LSTM–DNN [10], and LSTM/BiLSTM architectures [11] have shown promising performance in modeling sea-level dynamics, including applications in Indonesian coastal regions [12].

Although improvements in predictive performance have been widely reported, many existing studies mainly emphasize accuracy metrics while giving limited attention to data distribution characteristics. Sea-level datasets frequently exhibit imbalanced patterns where extreme events occur less often than normal conditions. This imbalance may lead learning models to prioritize dominant patterns, reducing their ability to capture rare but critical events. Previous studies indicate that oversampling strategies can improve model performance when dealing with imbalanced data distributions [13], [14]. Furthermore, deterministic prediction alone may be insufficient to represent uncertainty associated with climate variability and extreme ocean conditions [5]. Therefore, probabilistic modeling approaches are increasingly required to better capture prediction uncertainty.

Bootstrap-based resampling methods provide a statistical framework for improving data representation by generating multiple training samples while preserving the inherent characteristics of the original dataset. In time-series analysis, Moving Block Bootstrap

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(MBB) is particularly suitable because it maintains temporal dependence by resampling consecutive observation blocks rather than independent points [17], [18]. Earlier theoretical studies highlight that bootstrap techniques for dependent observations are essential for maintaining statistical consistency in time-series analysis [19]. In addition, appropriate block-length selection plays a critical role in achieving reliable bootstrap performance for dependent data [20]. Bootstrap approaches have been successfully applied to construct predictive distributions in LSTM-based models [15] and to estimate epistemic uncertainty in sequential data [16]. These characteristics make MBB a relevant choice for environmental and oceanographic applications where temporal correlation plays a critical role.

Based on these considerations, this study proposes a hybrid Bootstrap–LSTM framework for probabilistic sea-level prediction along the southern coast of Java. The proposed approach integrates Moving Block Bootstrap with LSTM to enhance data representation, reduce bias caused by imbalanced observations, and preserve temporal structure in sequential data. By combining statistical resampling with deep learning, this framework is expected to improve model stability, increase predictive reliability, and provide a more robust approach for analyzing complex marine dynamics under environmental uncertainty.

THEORITICAL FRAMEWORK

Sea-level dynamics can be represented as a nonlinear stochastic time-series process influenced by atmospheric forcing, ocean circulation, tidal harmonics, and climate variability. Let the observed sea-level sequence be denoted as $\{X_{\#}\}^{\&}_{\#\$\%}$, where $X_{\#}$represents sea level at time t. Such processes typically exhibit temporal dependence, nonstationarity, and heavy-tailed behavior due to rare extreme events, requiring predictive models that capture nonlinear temporal structure as well as uncertainty.

Long Short-Term Memory (LSTM), a gated recurrent neural network, is designed to model sequential data with long-term dependencies. Given an input sequence, the LSTM state is updated through gating mechanisms defined as:

$$f\# = \sigma\text{-}W'(! + U'h\#!\% + b'3, \qquad i\# = \sigma\text{-}W)(! + U)h\#!\% + b)3,$$
$$c7\# = \tanh\text{-}W*(! + U*h\#!\% + b*3,$$
$$c\# = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \; h_t = o_t \odot tanh(c_t), \tag{1}$$

where $x_{\#}$denotes the input vector, $h_{\#}$the hidden state, and $c_{\#}$the memory cell state. The prediction is obtained through an output mapping $X\text{D}_{\#+\%} = g(h_{\#})$. This structure enables LSTM to approximate nonlinear temporal functions and capture long-term dependencies in sea-level data. However, predictive accuracy depends on the representativeness of training data, and rare extreme observations may lead to biased estimations.

To enhance data representation and quantify predictive uncertainty, Moving Block Bootstrap (MBB) is employed. Unlike classical bootstrap, which assumes independence, MBB preserves temporal dependence by resampling consecutive blocks of length l. For a time series $\{X_{\%}, X_{,}, \ldots, X_{\&}\}$, overlapping blocks are constructed as $B_{-} = (X_{-}, X_{-+\%}, \ldots, X_{-+.!\%})$, $j = 1, \ldots, n - l + 1$, and bootstrap samples are generated by randomly selecting and concatenating these blocks. Each resampled dataset produces a prediction $X\text{D}_{\#*+}{}^{(1}{}_{\%}{}^{)}$, $b = 1, \ldots, B$, and the predictive distribution is estimated as

$$F\text{D}(x) = \frac{1}{B}\sum_{b=1}^{B} I\left(\hat{X}_{t+1}^{*(b)} \leq x\right), \tag{2}$$

where $I(\cdot)$is the indicator function. By combining nonlinear temporal modeling through LSTM with statistically consistent dependent resampling via MBB, the proposed framework improves parameter stability, reduces bias from data imbalance, and enables probabilistic sea-level forecasting under climate-driven uncertainty.

RESEARCH METHODOLOGY

This study uses sea level time series data obtained from the Copernicus Marine Service open data platform. This dataset covers the observation period from January 2018 to August 2, 2025, representing sea level measurements used for sea level prediction analysis. All data processing and model implementation were performed using the Python programming language within the Google Colaboratory environment.

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The dataset underwent preprocessing to ensure data quality and suitability for time series forecasting prior to model development. The preprocessing stage included data cleaning, normalization, and transformation of the time series into a sequential input-output format compatible with Long Short-Term Memory (LSTM) models. The preprocessed dataset was then divided into training and testing subsets using an 80:20 ratio, with 80% of the data used for model training and 20% reserved for model evaluation.

This study evaluates whether the integration of Moving Block Bootstrap (MBB) improves the prediction performance and uncertainty representation of LSTM in sea level forecasting by comparing the results of a standard LSTM model and a hybrid MBB–LSTM model.

The research stages are summarized as follows:

a. Data acquisition and exploratory analysis, including the collection and initial examination of sea level time series data.
b. Data preprocessing and normalization to clean the dataset and scale the data for model training.
c. Moving Block Bootstrap resampling to generate a resampled dataset while preserving the temporal dependency structure of the time series.
d. Data separation into training and testing subsets.
e. LSTM model development, including the construction of input, hidden, and output layers.
f. MBB–LSTM hybrid modelling, where the bootstrap-resampled dataset is used to train multiple LSTM models.
g. Model evaluation and comparison, where predictions from the standard LSTM and MBB–LSTM models are compared with observed values using statistical accuracy metrics.

Finally, the prediction results generated by both models are analyzed to evaluate the effectiveness of the proposed hybrid framework in improving sea level forecasting performance. The overall research workflow is illustrated in Fig.I. Research workflow of the proposed Hybrid Moving Block Bootstrap–LSTM framework for sea-level prediction.

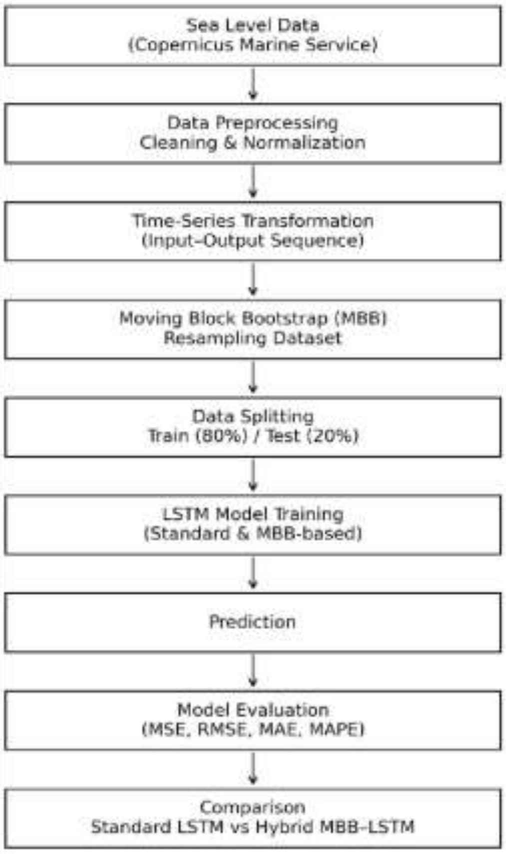

Figure I. Research workflow of the proposed Hybrid Moving Block Bootstrap–LSTM framework for sea-level prediction.

RESULTS AND DISCUSSION

In this study, sea level prediction was conducted using two approaches, namely the standard Long Short-Term Memory (LSTM) model and a hybrid model combining Moving Block Bootstrap (MBB) with LSTM. The LSTM model was first applied to capture the temporal patterns of sea level variability from historical time-series data. The prediction performance of the LSTM model was evaluated using several statistical metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

Table 1. Comprehensive Result of MSE, RMSE and MAPE

Model	MSE	RMSE	MAE	MAPE (%)
LSTM	2.11×10^{-5}	0.00459	0.00356	0.34
Hybrid MBB–LSTM	0.01155	0.10749	0.08370	8.99

The evaluation results showed that the LSTM model achieved very high prediction accuracy, with an MSE of 2.11×10^{-5}, an RMSE of 0.00459, an MAE of 0.00356, and a MAPE of 0.34%. The very low MAPE value indicates that the predicted sea level values are very close to the observed data, indicating that the LSTM model is able to effectively capture nonlinear temporal patterns in sea level fluctuations. The LSTM prediction results, illustrated in Figure II, show that the predicted values closely follow the observed sea level dynamics during the testing period. To further improve prediction robustness and incorporate uncertainty estimates, a hybrid approach combining Moving Block Bootstrap with LSTM was implemented. The Moving Block Bootstrap method is used to generate multiple resampled datasets that preserve the temporal dependence structure of the time series. These bootstrap samples are then used as input to the LSTM model to generate probabilistic predictions.

The performance evaluation of the hybrid MBB–LSTM model yielded an MSE of 0.01155, an RMSE of 0.10749, an MAE of 0.08370, and a MAPE of 8.99%. Although the error values were higher than those obtained from the standard LSTM model, the hybrid approach provided additional information in the form of prediction uncertainty through confidence interval estimation. This probabilistic framework allows the model to represent the variability of possible future sea level values rather than producing a single deterministic prediction.

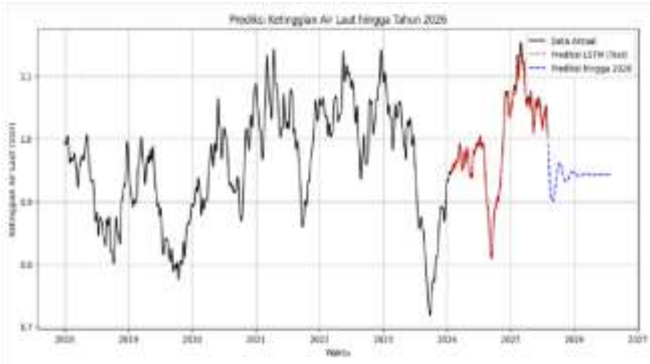

Figure II. The Result of LSTM

Figure III. The Result of Hybrid

The prediction results of the hybrid model are illustrated in Figure III, where observed sea level data are displayed along with predicted values and 95% confidence intervals obtained from bootstrap resampling. The shaded areas represent the distances close to the predictions, indicating possible upper and lower limits of future sea level variations. The predicted sea level through 2026 exhibits relatively stable fluctuations around the latest observed values, indicating that no extreme sea level anomalies are expected within the forecast range. In addition to the prediction analysis, a trend analysis was performed to examine the long-term trend of sea level change in Figure IV.

Figure IV. Sea Level Rise Trend

A linear regression trendline fitted to the combined observed and predicted data indicates a gradual sea-level rise trend. The estimated slope of the trendline corresponds to a sea-level rise of approximately 0.00744 meters per year, equivalent to 7.44 mm per year. table 2 shows the estimated sea-level rise trend. These results indicate a gradual sea-level rise over time despite shortterm fluctuations caused by oceanographic and climate variability. The estimated sea-level rise rate obtained in this study is slightly higher than the global average sea-level rise reported in previous studies, which is typically around 3–4 mm per year. However, regional sea-level changes can vary depending on local ocean dynamics, atmospheric conditions, and coastal processes. Therefore, these results highlight the importance of predictive modeling and uncertainty analysis for understanding future sea-level variability and supporting coastal management and mitigation strategies.

Table 2. Sea-Level Rise Trend Forecast

Parameter	**Value**
Sea level rise (m/year)	0.00744
Sea level rise (mm/year)	7.44
Observation period	2018 – 2025
Forecast period	2025 – 2026

The prediction performance of the standard LSTM model and the hybrid Moving Block Bootstrap–LSTM (MBB–LSTM) model is summarized in table 1. The standard LSTM model achieved lower error values compared to the hybrid model, with an MSE of 2.11 × 10!", RMSE of 0.00459, MAE of 0.00356, and MAPE of 0.34%. These results indicate that the deterministic LSTM model is highly accurate in fitting the observed sea level data. On the other hand, the hybrid MBB–LSTM model produced higher error values, with an MSE of 0.01155, RMSE of 0.10749, MAE of 0.08370, and MAPE of 8.99%. Although the hybrid model shows slightly lower predictive accuracy compared to the standard LSTM, it provides additional advantages by incorporating uncertainty estimation through bootstrap resampling. The hybrid approach allows the model to generate probabilistic predictions with confidence intervals, which are useful for representing the variability and uncertainty of future sea level changes.

Therefore, while the standard LSTM model provides highly accurate deterministic predictions, the hybrid MBB–LSTM model offers a more comprehensive framework by combining prediction capability with uncertainty quantification, making it suitable for probabilistic sea level forecasting.

CONCLUSION

This study presents a sea level prediction framework using a Long Short-Term Memory (LSTM) model and a hybrid Moving Block Bootstrap–LSTM (MBB–LSTM) approach. The LSTM model successfully captured the nonlinear temporal patterns of sea level variability and produced highly accurate deterministic predictions with an MSE of 2.11 × 10!", RMSE of 0.00459, MAE of 0.00356, and MAPE of 0.34%. To incorporate uncertainty in the prediction process, the hybrid MBB–LSTM model was applied by generating bootstrap resampled datasets that preserve the temporal dependence structure of the original time series. The hybrid model produced probabilistic forecasts with a 95% confidence interval, achieving an MSE of 0.01155, RMSE of 0.10749, MAE of 0.08370, and MAPE of 8.99%. Although the deterministic LSTM model yielded lower prediction errors, the hybrid approach provides additional advantages by representing uncertainty in future sea level predictions. The forecasting results indicate relatively stable sea level fluctuations until 2026, while the trend analysis reveals a gradual increase in sea level with an estimated rate of approximately 7.44 mm per year. These findings demonstrate that combining deep learning models with bootstrap-based probabilistic methods can provide more informative sea level forecasts, which are valuable for coastal monitoring and long-term climate adaptation planning. Future work may incorporate additional environmental variables such as sea surface temperature, atmospheric pressure, and tidal dynamics to further improve the robustness of sea level prediction models.

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