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Wave Downscaling Approach with TCN model, Case Study in Bengkulu, Indonesia

Dio Navialdy[1], Didit Adytia[2,*]
[1,2]School of Computing, Telkom University Bandung, Indonesia

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ABSTRACT

When conducting marine operations that rely on wave conditions, such as maritime trade, the fishing industry, and ocean energy, accurate wave downscaling is important, especially in coastal locations with complicated geometries. Traditional approaches for wave downscaling are usually obtained by performing nested simulations on a high-resolution local grid from global grid information. However, this approach requires high computation resources. In this paper, to downscale global wave height data into a high-resolution local wave height with less computation resources, we propose a machine learning-based approach to downscaling using the Temporal Convolutional Network (TCN) model. To train the model, we obtain the wave dataset using the SWAN model in a local domain. The global datasets are taken from the ECMWF Reanalysis (ERA-5) and used to train the model. We choose the coastal area of Bengkulu, Indonesia, as a case study. The results of TCN are also compared with other models such as LSTM and Transformers. It showed that TCN demonstrated superior performance with a CC of 0.984, RMSE of 0.077, and MAPE of 4.638, outperforming the other models in terms of accuracy and computational efficiency. It proves that our TCN model can be alternative model to downscale in Bengkulu's coastal area.

Corresponding Author:

Didit Adytia,
School of Computing, Faculty of Informatics, Telkom University Bandung
Jl. Telekomunikasi. 1, Terusan Buah Batu – Bojongsoang, Kabupaten Bandung, Indonesia. 40257
Email: adytia@telkomuniversity.ac.id

1. INTRODUCTION

Maritime activities, such as maritime trade, the fishing industry, and ocean energy, are highly dependent on ocean conditions, especially wave height conditions. Several factors may affect maritime activities, such as extremely high winds that result in high waves or cyclones that lead to very high waves. Especially for wave condition factors, an analyzable downscaling of ocean waves is indispensable in maritime activities to assist, reduce the possibility of accidents, and reduce the likelihood of accidents and losses resulting from accidents due to sea conditions [1]. Accurate characterization of local or high-resolution wave climate is required. Wave climate is usually characterized by two sources of observations, buoys and satellites, and results from numerical models or dynamical downscaling. Buoys have the disadvantage of short records and significant gaps, while satellites provide global coverage but have only been available since 1992. Therefore, downscaling, such as dynamical and statistical downscaling, is an excellent alternative to performing high-resolution simulations [2].

To perform the wave downscaling process, several numerical wave models have been employed by researchers in the last three decades. For simulating wave height, especially in coastal areas, a spectral wave model Simulating Wave Nearshore (SWAN) is preferable for downscaling. Alizadeh et al. [3] introduced a distributed wind downscaling method for modeling wave climate under future scenarios. This technique uses a regional climate model (RCM) to simulate wind fields at various resolutions, followed by a statistical correction method to adjust wind speed and direction. The corrected wind fields are then utilized as inputs for the SWAN wave model to predict wave parameters such as significant wave height, mean wave period, and mean wave direction. The study assesses the method's performance by comparing simulated wave parameters with observations and other wave models for the present climate.

Additionally, the technique is applied to project changes in wave climate for future scenarios (RCP4.5 and RCP8.5). The findings indicate that the method enhances wave simulations' accuracy and suggests significant future wave climate alterations, including higher waves and longer periods in specific regions. The study by Umesh [4] evaluates input-dissipation parameterizations in WAVEWATCH III, a third-generation wave model. Comparing results with a nested WAVEWATCH III-SWAN model in the Indian Seas sheds light on wave prediction accuracy vital for maritime activities and coastal engineering. The paper likely provides detailed insights into parameterization effects, guiding optimal wave simulation settings in the Indian Seas. In Björkqvist's paper [5], they compared WAM (Wave Action Model) with SWAN and WWIII. The WAM, among SWAN and WW3, is employed to simulate wave dynamics within Helsinki's coastal archipelago, utilizing a high-resolution grid and dual wind forcings. WAM exhibits favorable agreement with wave buoy measurements concerning significant wave height, showing minimal disparities in biases and root-mean-square-errors (RMSE) compared to other models. Notably, WAM tends to propagate long-wave energy more effectively into the archipelago, leading to heightened peak periods along the coast. These disparities mean peak periods between models can reach up to 1.4 seconds. However, WAM occasionally underestimates high-frequency wave energy under specific wind directions, potentially due to inadequate friction velocity. Furthermore, variations in the upper integration frequency contribute to biases in the mean period by approximately 1 second. While WAM effectively captures the spatial variability of the wave field within the archipelago, it encounters challenges in replicating temporal wave parameter variability. In a study by Martinez[6], it was explained that the dynamical downscaling approach requires significant computational power while also demanding a large amount of data as input. The implementation of this technique also emphasizes the need for a high level of expertise to ensure proper and effective interpretation of the resulting simulation results. Through an in-depth understanding of these constraints, it is hoped that this will help design and implement this method more efficiently when conducting ocean wave height simulations.

Machine learning has been applied extensively as a substitute for downscaling and enhancing earlier simulation models. For example, Kim [7] forecast one week in Hitachinaka Port, Japan, using six years of six-hourly data from the European Center for Medium-Range Weather Forecasts (ECMWF), National Oceanic and Atmospheric Administration (NOAA), and Japan Meteorological Agency (JMA). Kim employed the Group Method of Data Handling (GMDH) and Artificial Neural Network (ANN) as their two machine-learning techniques. Their work demonstrates that the machine learning framework for nearshore wave prediction may enable wave forecasts up to one week in advance and be applied to areas where nearshore wave observation data is accessible. Another ANN model used for downscaling is Long short-term memory (LSTM). In a study conducted by Wei [8], two years of metrological data from NOAA were used to train the LSTM model on the Atlantic Coast of the United States, demonstrating that Artificial Neural Networks (ANNs) are capable of functioning well and are free from overfitting and underfitting issues; short-term forecasts (one to six hours) yield more accurate results than long-term predictions (24 to 48 hours). In the paper of Adytia et al. [9] using a more recent model, namely Bidirectional Long short-term memory (Bi-LSTM) with results with 14-day prediction results with a correlation coefficient (CC) score of 0.97, an RMSE score of 0.16, and a mean absolute percentage error (MAPE) score of 11.79. In the paper of Atiko & Adytia [10], they used the Transformers model to perform wave downscaling. Here, they were able to get the accuracy of the model with a CC performance of 0.96, an RMSE score of 0.16, and a MAPE score of 11.79. Zhang's study [11] showed that the Temporal Convolutional Network (TCN) can outperform the LSTM model for forecasting Traffic Flow. Wehage's study [12] compares machine learning models for weather forecasting, highlighting the TCN as a standout model. The TCN outperformed other models in six out of ten parameters when predicting weather conditions. This indicates its superior ability to effectively capture the nonlinear interrelationships among weather parameters and handle multivariate and sequential data. The TCN's architecture, which includes dilated convolutions, allows it to process long-range patterns and provides a significant advantage over traditional models that do not encode sequential information. The results suggest the TCN is a promising tool for accurate and fine-grained localized weather forecasting. In this research, we propose to model wave downscaling by using the TCN model. We choose a case study of the coastal area of Bengkulu, Indonesia, which its coastal area directly faces the open Indian Ocean. In this area, waves are dominated by swell.

In this study, we suggested performing downscaling from a global grid using a machine learning technique to use the TCN to gain higher resolution. We train the TCN downscaling model using the spatial-temporal data of hourly waves in Bengkulu, Indonesia. By utilizing the SWAN model for spectral wave simulation, local wave height data are obtained by utilizing the global wave height data from ERA-5 (ECMWF). To get the best accuracy for downscaling using machine learning, we perform feature selection using a spatial correlation approach, in which we select the best location of wave global data as a feature for machine learning prediction, i.e., using TCN. Results of simulation are evaluated using CC, RMSE, and MAPE. Moreover, we also compare the results of TCN with the well-known Transformer and LSTM models. The aim of this research is to develop an improved model for simulating local wave patterns, which can be efficiently implemented in various locations across Indonesia with reduced computational costs and increased speed of the implementation of downscaling compared to the traditional downscaling model. The following section describes the method used to perform the proposed machine learning downscaling approach.

2. METHOD

In this study, we employ the TCN model in a machine-learning method for wave downscaling in order to collect high-resolution ocean wave data. We achieve this by running numerical simulations with the SWAN model, which allows us to create a dataset of waves. First, we use global wind data from ERA5 reanalysis from ECMWF as input for the SWAN model to perform nested wave simulations. The goal of these nested simulations is to gather high-resolution wave data in the research region, which is Indonesia's Bengkulu coast. The machine learning model uses the collected wave dataset as training data and uses a regression from global wave data to local wave data to calculate the downscaling. The ensuing sections provide a detailed description of these steps.

2.1. System Design

The stage of our System Design is depicted in Figure 1 below. Initially, we acquire the global and simulated wave data, which undergoes preprocessing and partitioning into Training and Dataset segments. Following this, we conduct Feature Engineering utilizing the training dataset. Upon achieving satisfactory outcomes, testing is conducted using the test dataset to procure High-Resolution Wave data and assess the results.

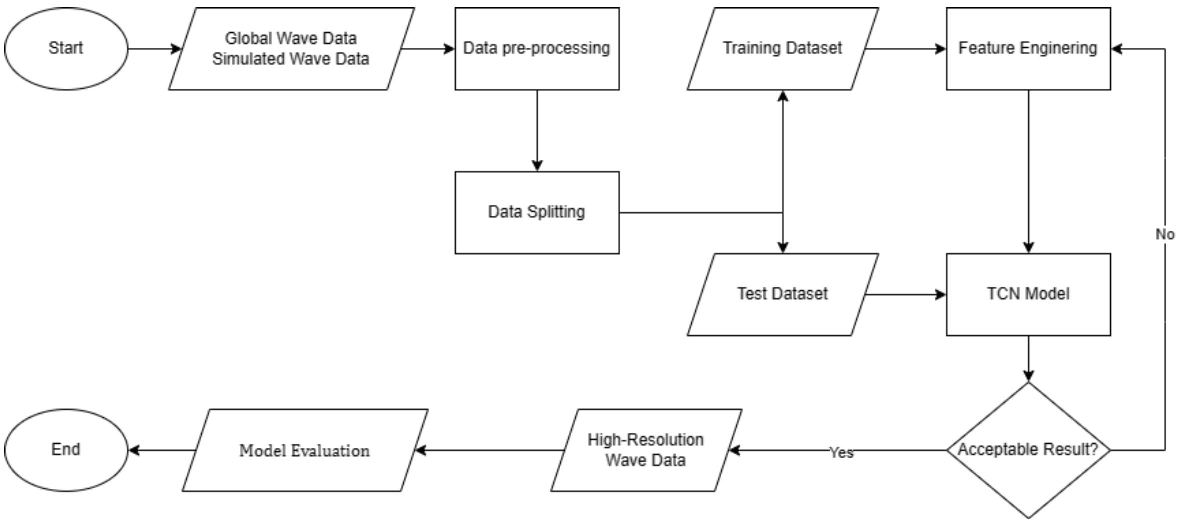

Figure 1. Flowchart of the machine learning-based downscaling by using the TCN model.

2.2. Global Wave Data

We use the global wave height data from ECMWF's ERA-5 [13] with a spatial grid resolution of 0.5° as the input for the downscaling TCN Model. Based on the global wave data, we use the SWAN model to simulate and use as the goal for high-resolution local wave data at 102°9'56.90" E and 3°51'27.28" S. Both of the data are from Bengkulu, Indonesia, as can be seen in Figure 3 and span from 2014 until 2022.

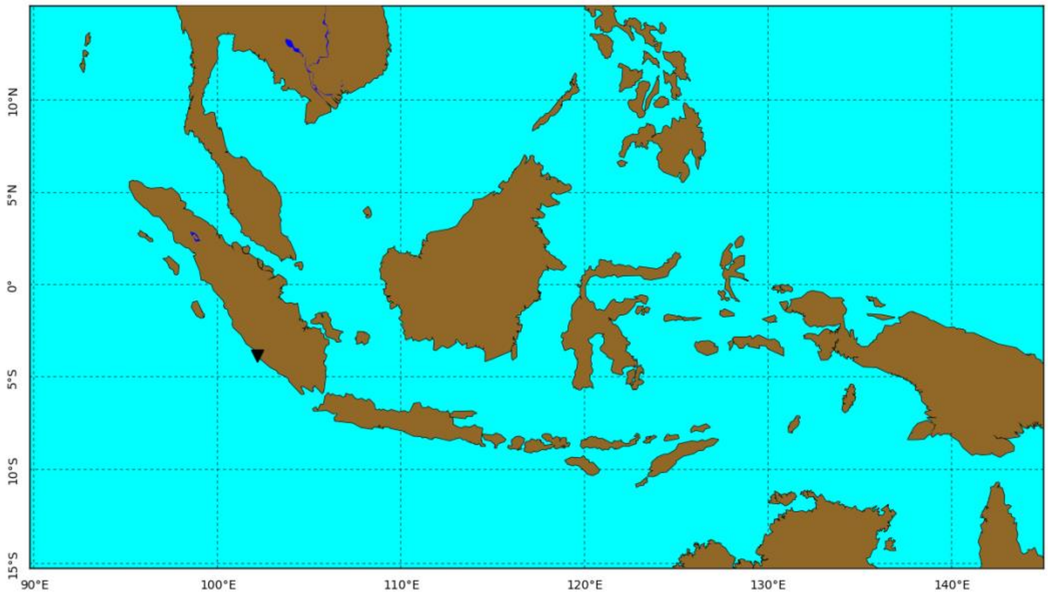

Figure 2. Location of study area in Bengkulu, Indonesia. The figure indicates the area for the wave simulation in the global domain.

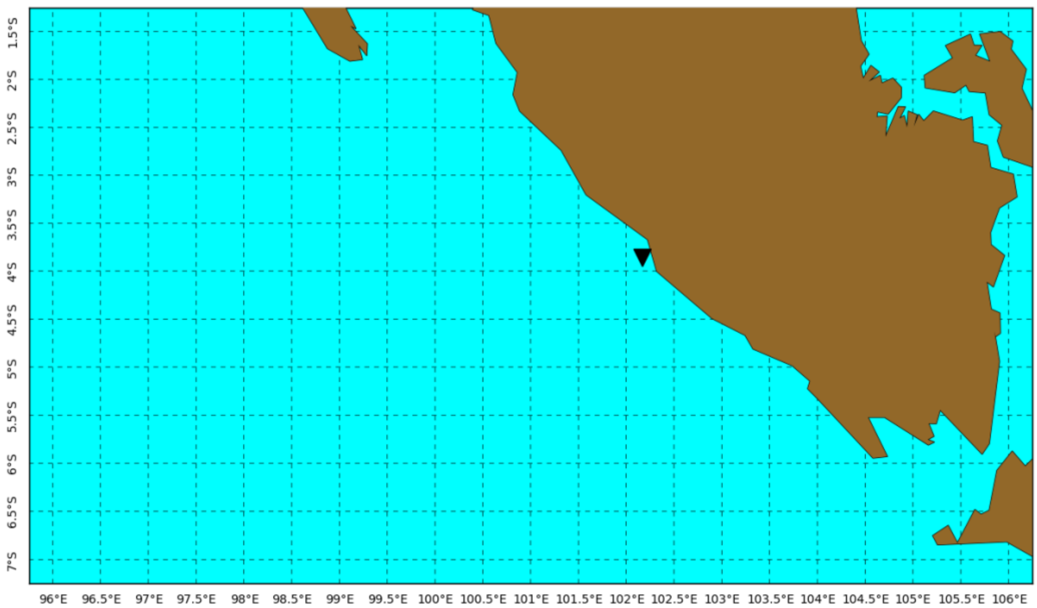

Figure 3. A zoom of the coastal area in Bengkulu, Indonesia. The triangle marker indicates the location of the local wave to be predicted in the downscaling process.

2.3. Simulated Wave Data

As mentioned, in this paper, we use the spectral wave model Simulating Waves Nearshore (SWAN) as a numerical wave model to construct local wave data that will later be the target for our downscaling. The model is used because it can consider various factors affecting waves, including wind force, tidal currents, wave boundary conditions, and Bathymetry [14]. It is designed to replicate waves in both shallow and deep oceans. [15].

2.4. Feature Engineering

To design an accurate machine learning-based wave downscaling, it is necessary to choose appropriate features as input for the machine learning model. Here, we apply features engineering technique by selecting locations with spatial correlation values, a statistical relationship between values measured at various locations within a region or geographic space of wave height data both in the global domain, and in the local domain. The spatial correlation attention method comprehensively examines the interconnections among variables and dynamically evaluates the significance of various variables within input data across varying time intervals [16]. Using Pearson's Correlation coefficient, the correlation coefficient (CC) between each wave data point from both the global domain and the local domain will be determined. Depending on the CC value, the CC values will be indicated as colored points. In addition to using spatial correlation, feature selection will be made based on the duration of the training data, which is two, four, six, and eight years long, respectively. In Boulmaiz's [17] study, the length of the training data has been shown to affect the model's performance.

2.5. Temporal Convolutional Networks (TCN)

In this paper we use the rather recent machine learning model called the Temporal Convolutional Networks or TCN to calculate prediction of wave downscaling. The TCN, as a 1D convolutional architecture, utilize a convolutional network, which is a convolution that only involves elements from the same or previous time in the last layer. TCN also uses Sequence Modeling, Causal Convolutions, and Dilated Convolutions to improve computational performance and long-term memory[18].

2.5.1. Causal Convolution

One of techniques used in the TCN is Causal Convolution where the goal to understand the patterns in a sequence of inputs $x_0, x_1, \dots, x_t$ to be able to predict the corresponding outputs $y_0, y_1, \dots, y_t$ at each time step also known as Sequence Modeling. When predicting the output y_t at a time t. it should only use information from previously observed inputs and not depend on the future input such as $t + 1$.

2.5.2. Dilated Convolutions

Dilated convolutions are a variant of convolutional operations where the kernel is expanded by introducing spaces between its elements. This enables the network to encompass a broader receptive field without augmenting parameter count or sacrificing resolution [19]. By employing dilated convolutions, information can be progressively integrated across various time blocks, facilitating the efficient utilization of a more extensive historical context [20]. This technique employs an exponential increase factor f, depending on the dilation coefficient C, with the formula:

$$f = C^l \tag{1}$$

Where l represents the hidden layer. This allows the kernel to operate at a coarser scale without losing resolution or coverage, as illustrated in Figure 4.

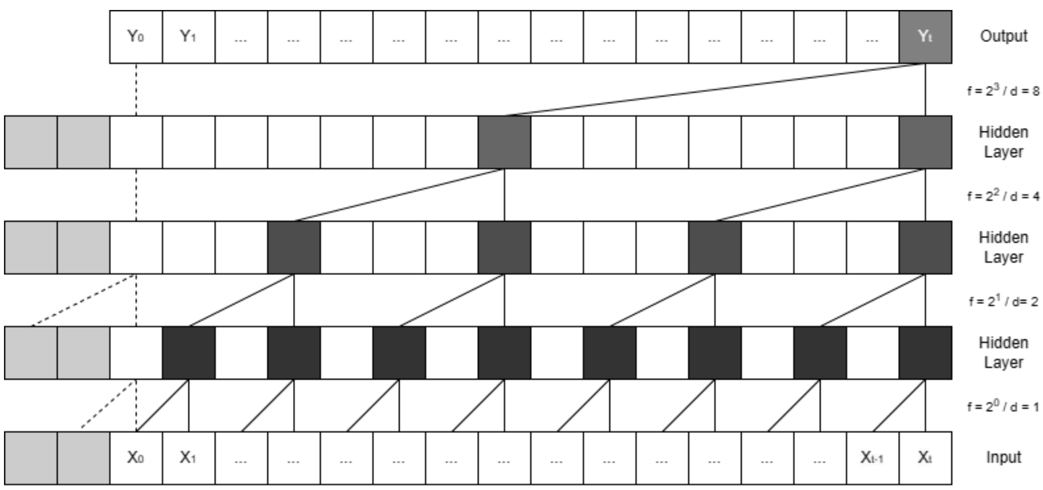

Figure 4. The architecture of the TCN model.

2.6. Model Evaluation

To calculate the performance of the model in predicting wave downscaling, we use three matrix evaluations, i.e., the RMSE, MAPE, and CC. The Pearson's Correlation Coefficient (CC) is defined as follows

$$CC(X,Y) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (2)$$

Here, the symbol n represents the sample size, which refers to the number of observations in the dataset. X_i denotes the value of the first sample, while $\bar{X}$ represents the mean of the first sample. Similarly, Y_i represents the value of the second sample, and $\bar{Y}$ denotes the mean of the second sample. The Root Mean Square Error (RMSE), and the Mean Averaged Percentage Error (MAPE) are defined as follows.

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

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \quad (4)$$

The symbol n represents the number of observations in the dataset. y_i denotes the actual value at observation i , while $\hat{y}_i$ represents the estimated value at observation i. By calculating the Pearson CC, RMSE, and MAPE between the downscaled wave data and the simulated wave data from SWAN, the TCN downscaling model's performance can be assessed.

3. RESULT AND DISCUSSION

In this section, we discuss the results of downscaling in Bengkulu's coastal areas. We perform the wave downscaling process by considering spatial correlation and length of training data as variables in the development of model feature engineering. The TCN models and the other models used to compare the results will be using the same computer to compute the model using GPU runtime with specification as follows; the CPU Intel i5 10500 H with 2.50 GHz boosted by overclocking, 16 GB of RAM, NVidia RTX 3050 with 4 GB GDDR5 VRAM, and NVMe Generation 3 as the data storage. In the next subsection, we first perform the spatial correlation test for our feature engineering.

3.1. Spatial Correlation

Spatial correlation is obtained by comparing the CC scores between the global and local waves. The spatial association was computed using wave height data spanning eight years. As shown in Figure 5, where triangles stand in for local wave and dots for global waves, the spatial correlation with CC > 0.0, we obtained 67 wave points, and in Figure 6, the spatial correlation with CC > 0.88, we obtained 34 wave points.

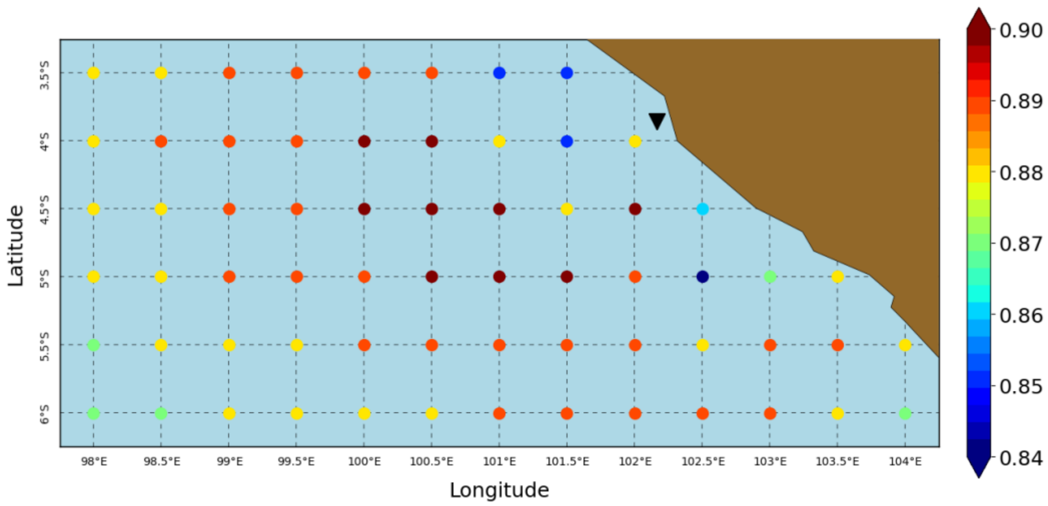

Figure 5. All points (CC > 0.0) of spatial correlation at Bengkulu, Indonesia

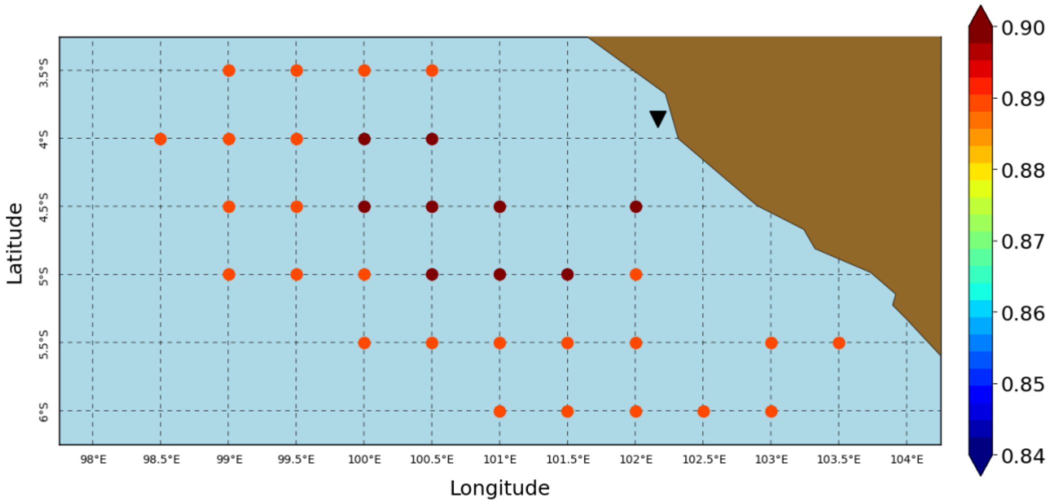

Figure 6. All points (CC > 0.88) of spatial correlation at Bengkulu, Indonesia

To find out how many wave points work best as inputs for the TCN downscaling model, we ran the experiments using the spatial correlation data. To test the model, 14 days ahead were predicted for every scenario involving spatial correlation. Then, we compared the results using CC, RMSE, and MAPE scores to determine which model performs the best.

As shown in Table 1, the downscaling performance with 67 global wave points with spatial correlation value CC > 0.0 is better than that with 34 global wave points with CC > 0.88. We will use the 67 global wave points as one of the features for TCN downscaling input and a reference for conducting the of training data test in the next section.

Table 1. Table result of TCN 14 days forecasting with various spatial correlation scenarios

Spatial Correlation	Wave Data Points	CC	RMSE	MAPE
$CC > 0.0$	67	**0.984**	**0.077**	**4.638**
$CC > 0.88$	34	0.981	0.123	9.46

3.2. Length of Training Data

With 42 years of available wave data in Bengkulu's coastal areas, it is imperative to conduct a test on the training data length to enhance our model's performance and efficiently downscaling the waves from the global to the local in Bengkulu's coastal areas. We conduct this test by configuring various data length scenarios. Specifically, we utilize training data spanning two, four, six, and eight years to assess the optimal TCN model performance setting.

Table 2. Table result of TCN 14 days forecasting with various length scenarios

Length of Training Data	CC	RMSE	MAPE
2 Years	0.946	0.382	30.679
4 Years	0.983	0.186	15.015
6 Years	0.977	0.086	6.042
8 Years	**0.984**	**0.077**	**4.638**

As shown in Table 2, eight years of training data length have the best result compared to the others having CC value of 0.984, RMSE value of 0.077, and MAPE value of 4.638. We will use eight years of data training as the input of the TCN model for downscaling in Bengkulu's coastal areas.

3.3. Comparing Model

In this section, we will compare the results of our model and some other models with the result of wave data in Bengkulu's coastal areas. The different models that are used for comparison are Transformers and LSTM. Each model also features engineers like the TCN model to have a fair result. 14-day prediction is used for comparing the models and the actual wave data.

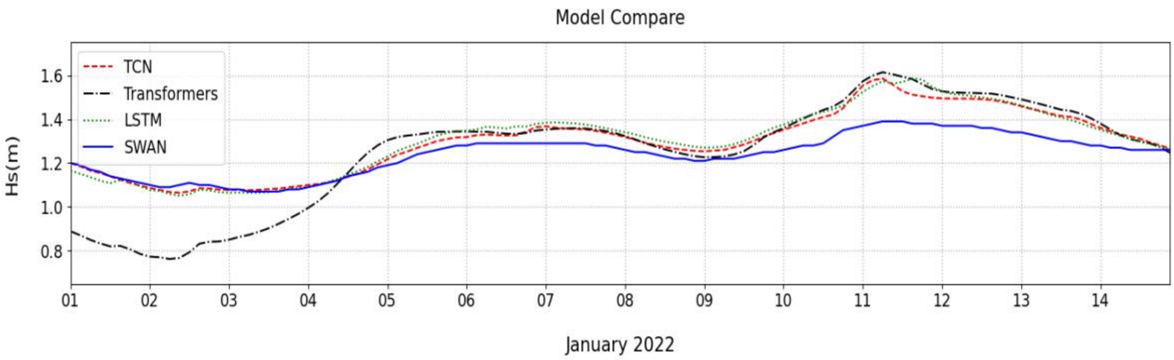

Figure 6. A comparative analysis of results of prediction by using several machine learning models, i.e., the TCN(Red), Transformers(Black), LSTM(Green), and SWAN(Blue) results

As shown in Figure 6, the results of both the TCN and the LSTM are relatively precise. However, we still need to compare models that perform better and have faster computation speeds compared to other models. We include the table for comparison as follows.

Table 3. Table result 14 days downscaling using TCN, Transformers, and LSTM

Model	Wave Data Points	Length of Training Data	CC	RMSE	MAPE	Training Duration
TCN	67	8 Years	0.984	**0.077**	**4.638**	**1 min 24 sec**
Transformers	34	8 Years	0.934	0.159	10.696	9 min 3 sec
LSTM	67	2 Years	**0.985**	0.089	5.684	1 min 38 sec

As shown in Table 3, the TCN model outperforms other models in terms of results, and the TCN model also demonstrates superior computation speed compared to LSTM and Transformers when handling larger datasets.

3.4. Discussion

The outcomes of our analysis align with prior research findings, demonstrating the superior performance of the TCN model over the LSTM model [11], [12]. The TCN model excels in CC, RMSE, and MAPE and demonstrates marginally faster computation compared to LSTM. In Shamshirband's paper [21], the comparison between the Machine Learning models and the SWAN model demonstrates that the ANN outperforms the SWAN model regarding computational efficiency, input requirements, and implementation. Specifically, the TCN, which is a type of ANN used in our research, yielded results comparable to the SWAN model in the coastal areas of Bengkulu. This indicates that the TCN model is capable of effective downscaling in Bengkulu's coastal areas and potentially in other regions of Indonesia.

4. CONCLUSION

This paper presents a machine learning-based downscaling method to provide high-resolution wave downscaling for complex locations in Bengkulu's coastal areas. The method uses local wave data from nested simulations of the SWAN for the TCN downscaling model in addition to global wave height ERA-5 from ECMWF. Finding areas with strong spatial correlation values achieved by calculating the CC between global and local wave height data makes feature selection. It was found that the downscaling model's results are strongly influenced by the length of the training data for our TCN model. Optimal performance for the TCN model is achieved with a training data duration of 8 years and encompassing 67 global points that are selected as features for the model. The result was a CC value of 0.984, an RMSE value of 0.077, and a MAPE value of 4.638. Which resulted in better results than the model we compared it with. While the difference is significant compared to Transformers, the TCN model has a relatively small difference in performance but shows substantial differences with the data input difference. The TCN model is relatively accurate for downscaling in Bengkulu's coastal areas. Therefore, TCN can be used as the alternative for downscaling for Bengkulu's coastal areas, which have relatively high performance and low computation cost compared to the SWAN model.

Nonetheless, it's important to note a limitation of this study: the utilization of a relatively limited set of global data points and lack of computation power, potentially constraining the generalizability of our findings. Additionally, our study solely compares the proposed method with two other deep learning models, excluding alternative downscaling models or other machine-learning-based approaches, and our data is limited only to Bengkulu's coastal areas. We hope that the next study will optimize the TCN model and try to use the model in different regions of Indonesia or across the globe.

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