JOIN (Jurnal Online Informatika)
p-ISSN: 2528-1682, e-ISSN: 2527-9165
Volume 9 Number 1 | June 2024: 61-69
DOI: 10.15575/join.v9i1.1312

# Water Level Rise Forecasting Using TCN Study Case in Surabaya Coastal Area

**Deni Saepudin[1], Egi Shidqi Rabbani[2], Dio Navialdy[3], Didit Adytia[4]**
[1,2,3,4]School of Computing, Telkom University Bandung, Indonesia

**Article Info**

***Article history:***

Received February 28, 2024
Revised March 17, 2024
Accepted March 18, 2024
Available Online April 23, 2024

***Keywords:***

Water level rise
Coastal area
Water level forecasting
Machine learning
TCN

**ABSTRACT**

Climate change is causing water levels to rise, leading to detrimental effects like tidal flooding in coastal areas. Surabaya, the capital of East Java Province in Indonesia, is particularly vulnerable due to its low-lying location. According to the Meteorological, Climatological, and Geophysical Agency (BMKG), tidal flooding occurs annually in Surabaya as a result of rising water levels, highlighting the urgent need for water level forecasting models to mitigate these impacts. In this study, we employ the Temporal Convolutional Network (TCN) machine learning model for water level forecasting using data from a sea level station monitoring facility in Surabaya. We chose the TCN due to its ability to capture long-range dependency in sequential data and its ease of implementation. We divided the training data into three scenarios: 3, 6, and 8 months to train TCN models for 14-day forecasts. The 8-month training scenario yielded the best results. Subsequently, we used the 8-month training data to forecast 1, 3, 7, and 14 days using TCN, Transformers, and the Recurrent Neural Network (RNN) models. TCN consistently outperformed other models, particularly excelling in 1-day forecasting with coefficient of determination ($R^2$) and RMSE values of 0.9950 and 0.0487, respectively. The contribution of the study is the development of deep learning TCN to predict water levels in coastal areas of Surabaya, which has the potential to be implemented in other locations in Indonesia.

***Corresponding Author:***

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

## 1. INTRODUCTION

The increase in water levels is one of the many changes caused by climate change [1]. Although this rise happens slowly, it is happening faster now and has serious impacts [2], [3], and [4]. Due to their typical flat terrain and low elevations close to the water's surface, coastal areas are particularly vulnerable to the rise in water levels [5]. Surabaya, the capital city of East Java, predominantly lies in a low-lying area with altitudes ranging from 3-6 meters above water level, while its southern part exhibits higher elevations, reaching 20-50 meters above water level [6]. According to the Meteorological, Climatological, and Geophysical Agency (BMKG), Surabaya's coastal areas experience tidal flooding every year due to rising water levels [5]. In some years, the risk of flooding is four to five times higher than usual. This poses a serious threat to the coastal community. To prevent further losses, it is essential to take measures against tidal flooding caused by water level rise, and one effective approach is through water level forecasting.

Water level forecasting is important to help us predict how water levels will increase in the future, allowing us to minimize the impact of rising water levels, such as flooding in coastal areas [7]. Water level data is also essential for port operations, particularly in scheduling ship transportation and managing port services efficiently [8]. Additionally, past records of water level are fundamental for the design and construction of coastal and offshore infrastructure, while precise forecasts of water level are indispensable for planning and executing construction activities for these structures [9]. Tidal Harmonic Analysis (THA) is a traditional method for water level forecasting. It involves decomposing water level data into harmonic components using the Least Squares Estimation (LSE) based on observed data. However, THA is limited to predicting only tidal components and relies on extensive historical data [10].

Various approaches have been suggested to enhance the accuracy of THA in water level forecasting, such as employing multivariate least-squares harmonic estimation [11] and integrating the LSE method with the Inaction Method (IM) [12]. For water level prediction, other methods based on time series analysis have also been used. These include ARIMA (Autoregressive Integrated Moving Average) [13], SARIMA (Seasonal Autoregressive Integrated Moving Averaged) [14], and Holtz-Winters Exponential Smoothing [15]. ARIMA achieved a root mean square error (RMSE) of 0.270 for one-day-ahead prediction, while SARIMA and the Holt-Winters approach yielded RMSE values of 0.155 and 0.134, respectively, for seven-day-ahead forecasting. These results highlight the ongoing need to identify a model capable of achieving greater forecasting accuracy. An effective strategy for enhancing predictive models involves leveraging machine learning, a relatively novel approach. Ishida et al. (2020) [16] conducted a study in which they looked at the use of machine learning for forecasting water levels. Specifically, Long Short-Term Memory (LSTM) was employed to forecast water levels at the Osaka Gauging Station in Japan, resulting in the highest accuracy with an Nash-Sutcliffe efficiency (NSE) value of 0.720 for the forecasting period of 2016-2018. In a study conducted by Pan et al. (2020) [17], a model combining Gated Recurrent Unit (GRU) and Convolutional Neural Network (CNN) was developed for precise water level forecasting. The results showed that the GRU-CNN model did better than other machine learning models, even the LSTM model. It had the highest accuracy, with an NSE value of 0.9966 for a 5-day forecasting period. While GRU and CNN models offer high forecasting accuracy, they suffer from a notable drawback: high memory requirements during training. However, in 2018, Bai et al. introduced a solution to this issue with their Temporal Convolutional Network (TCN), which features shared filters across a layer, resulting in reduced memory requirements [18]. As a result, TCN holds promise for accurate water level forecasting.

Temporal Convolutional Network (TCN), which was introduced by Bai et al. in 2018, is a deep neural network architecture designed for processing time series data [19], [20]. TCN has been widely employed in various time series challenges, consistently demonstrating strong performance and yielding favorable outcomes. A study conducted by Hewage et al. in 2020 [21] explored the use of TCN for weather forecasting using data collected from local weather stations. The findings revealed that TCN outperformed LSTM and other traditional machine learning methods in terms of forecasting accuracy. Benitez et al. (2020) employed the Temporal Convolutional Network (TCN) to forecast energy demand in Spain, demonstrating its superior forecasting accuracy compared to LSTM models [22]. While TCN has shown promising accuracy in numerous forecasting applications, its adoption for water level prediction remains limited.

The objective of this paper is to design a precise water level forecasting model using machine learning techniques. Specifically, we employ Temporal Convolutional Networks (TCN) for this purpose and compare its performance with other contemporary machine learning models, including transformers and RNN. The selected case study is Surabaya in Indonesia, characterized by its low-lying terrain, where the coastal areas are prone to tidal flooding due to rising water levels [5]. The contribution of this research is to find a better algorithm to predict the water level that could be implemented in other locations in Indonesia due to the many cities with similar conditions.

## 2. METHOD

### 2.1. Design System

In this study, we utilized water level data obtained from the sea level monitoring facility provided by UNESCO for the location of Surabaya, Indonesia. During pre-processing, we addressed spikes and outliers within the data and handled missing values through interpolation. Subsequently, the dataset was divided into training and testing subsets, and the TCN model was trained using the training data. The model was then evaluated for forecasting performance, with several scenarios tested, varying the forecast horizon from 1 to 14 days. If the forecasting accuracy doesn't meet the expected result, hyperparameter tuning is conducted to improve model performance. Finally, we compared the forecasting accuracy of the TCN model with other machine learning models using the coefficient of determination and Root Mean Squared Error metrics. These steps are illustrated in Figure 1.

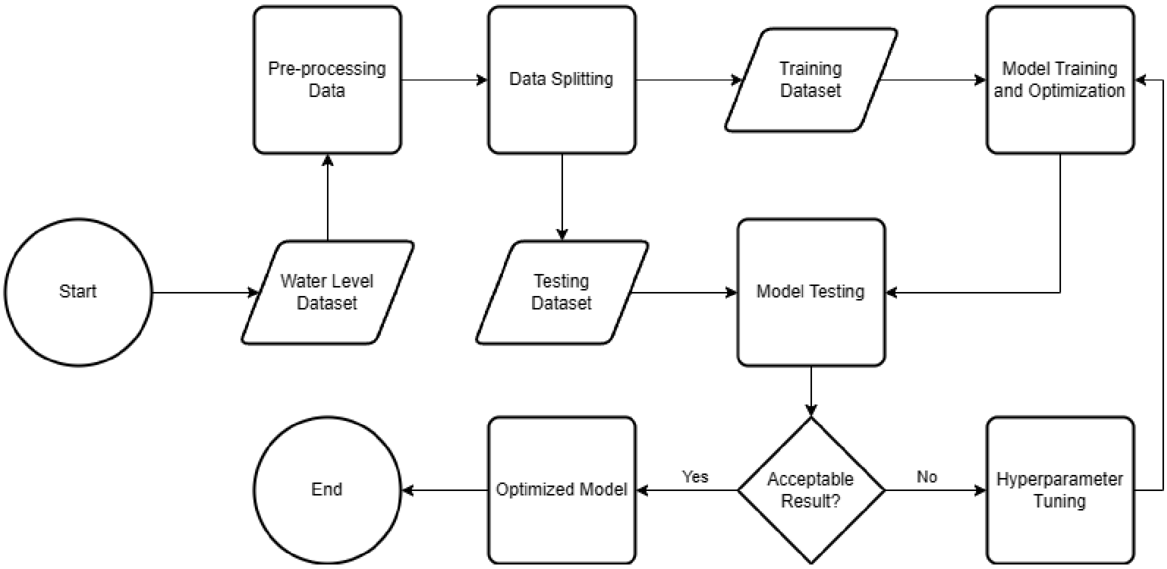


Figure 1. Flowchart of the TCN-based water level forecast

### 2.2. *Water Level Data*

The water level data utilized in this study was sourced from the sea level station monitoring facility provided by UNESCO. The station is situated in the northern region of Surabaya, Indonesia, with coordinates between -7.19996944 latitude and 112.74058611 longitude, as depicted in Figure 2. This dataset is publicly accessible online through the following link: [https://www.ioc-sealevelmonitoring.org/station.php?code=sura](https://www.ioc-sealevelmonitoring.org/station.php?code=sura).

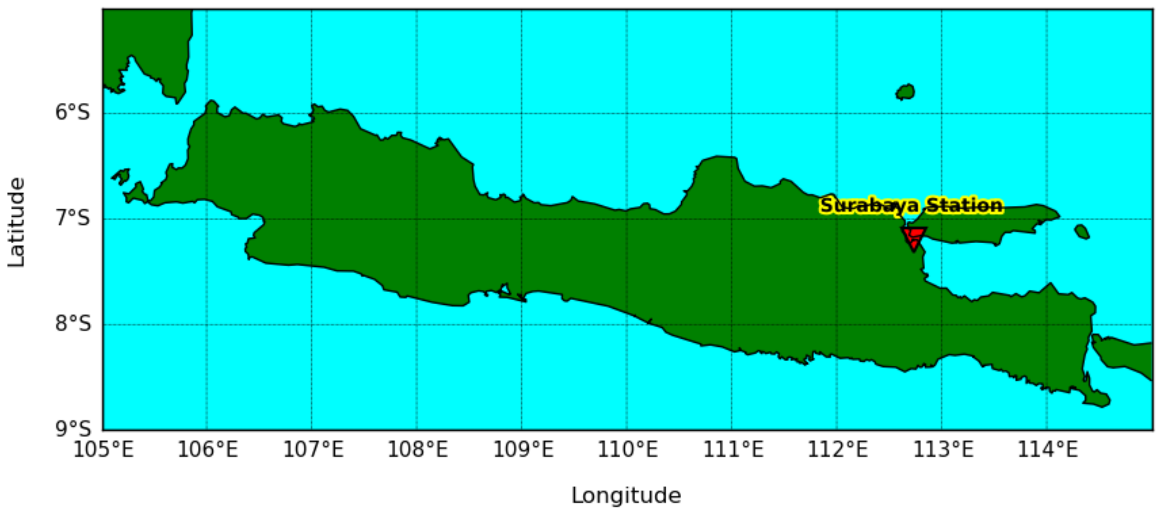


Figure 2. Location of the water level station monitoring facility in Surabaya

### 2.3. *Pre-Processing*

To ensure the reliability and usability of the water level data, we conducted a series of preprocessing steps. These steps were designed to handle missing values, outliers, and spikes, as well as to resample and interpolate the data. This process aimed to generate high-quality input data suitable for the machine learning model.

The raw water level data can be seen in Figure 3. It is recorded at three-second intervals, spanning from March 1, 2023, to December 25, 2023. In water level forecasting, utilizing such detailed period intervals in the data may introduce unnecessary harmonic components, potentially impacting forecasting accuracy. To address this, we transformed the raw water level data into hourly intervals.

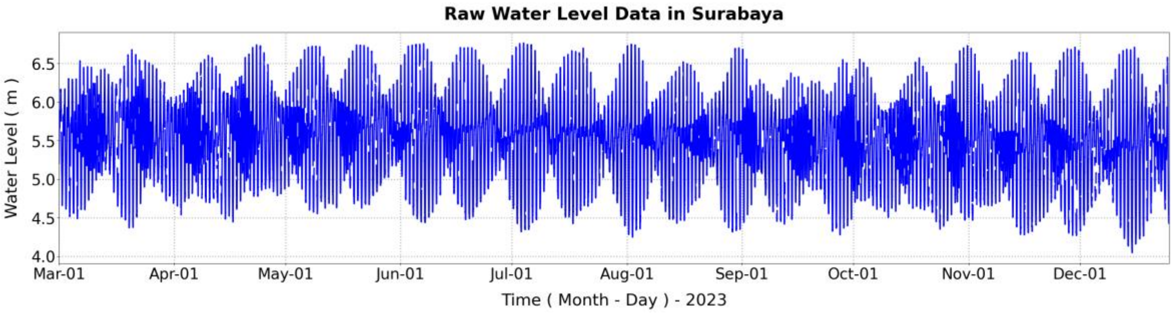

Figure 3. Plot of raw water level data in Surabaya

Next, we established threshold values to detect spikes within the data. The first threshold value was determined by adding three times the standard deviation to the mean water level, while the second threshold value was determined by subtracting three times the standard deviation from the mean water level. Any water level exceeding the first threshold value or falling below the second threshold value was identified as a spike, and these spikes were subsequently removed. Subsequently, rolling window statistics are computed to evaluate the median and standard deviation of the water level using a 6-hour window. Through this process, outliers are identified and subsequently removed, enhancing the dataset's reliability. However, addressing spikes and outliers in the data leads to the creation of additional missing values. To that end, we identified empty values within the dataset to pinpoint periods of missing data. The plot displaying the water level data alongside the flagged missing values is depicted in Figure 4.

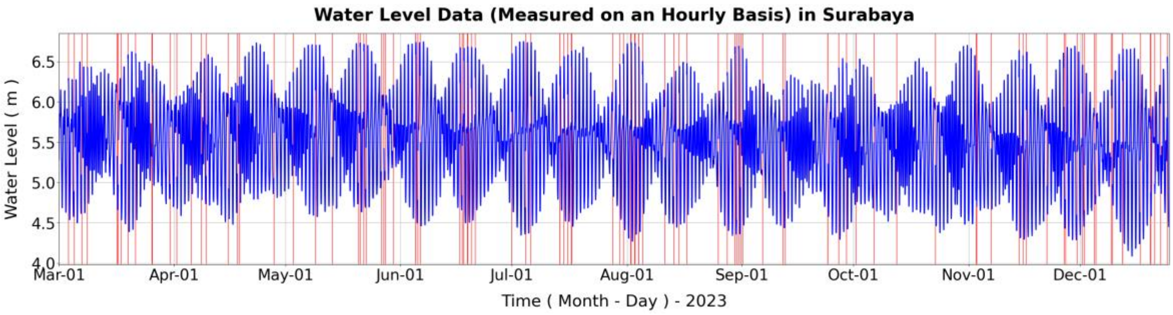

Figure 4. Plot of resampled water level data with flagged missing values (red bars)

The final step of data pre-processing involves addressing missing values through cubic interpolation, resulting in the processed data depicted in Figure 5. Additionally, the preprocessed data is partitioned into training and testing datasets, as illustrated in Figure 6. We partitioned the training dataset into three distinct periods: 3 months (from September 11, 2023, to December 11, 2023), 6 months (from June 11, 2023, to December 11, 2023), and 8 months (from April 11, 2023, to December 11, 2023). This division aims to evaluate the sensitivity of the training data to the model's performance and optimize the training dataset for improved model accuracy.

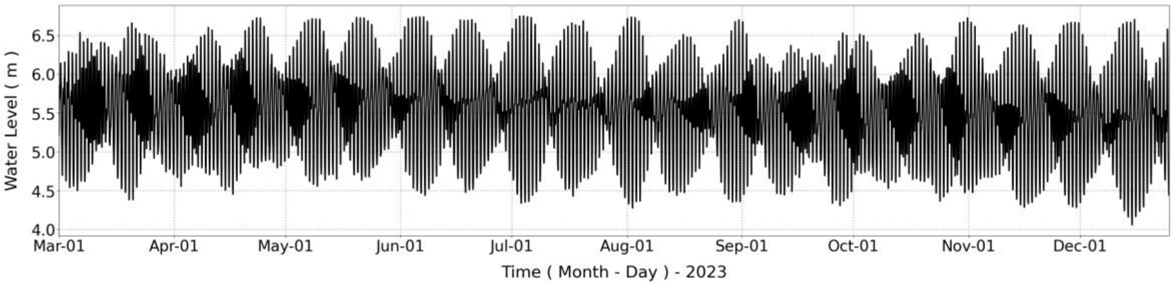

Figure 5. Plot of the processed hourly water level data with no missing values

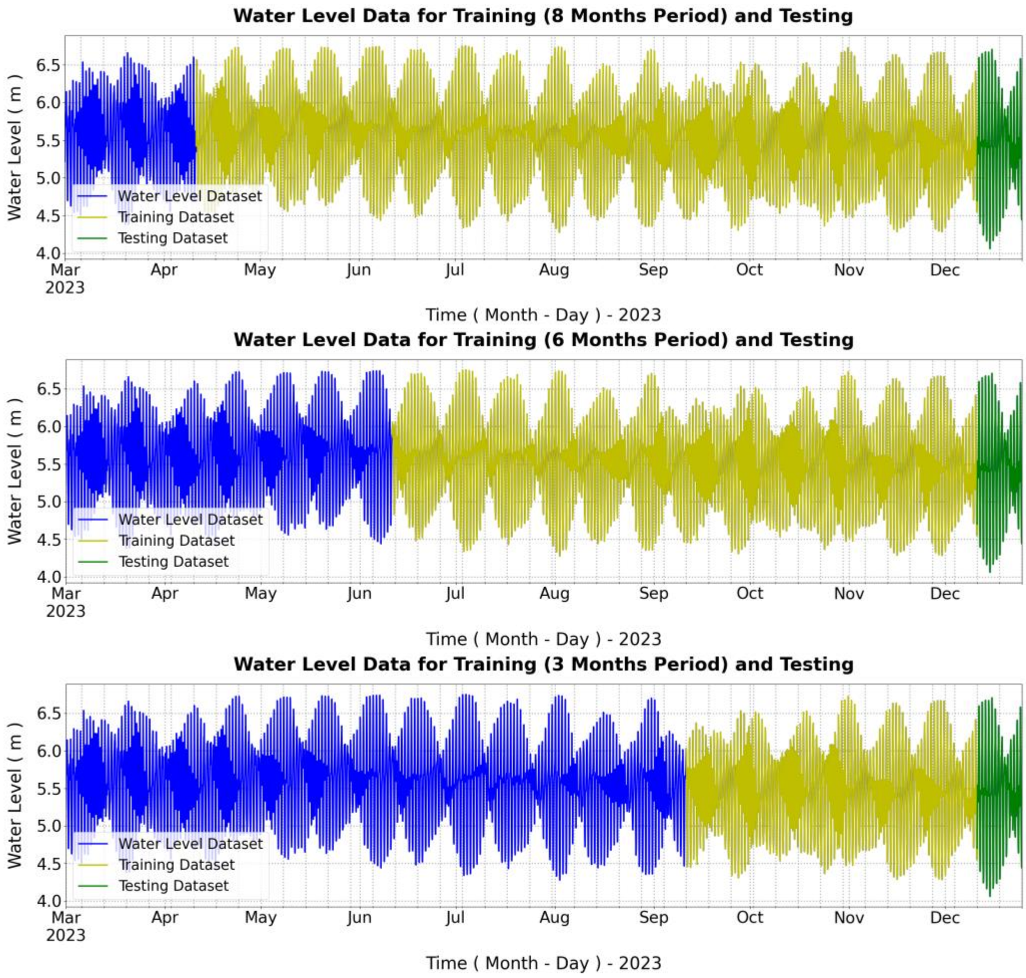


Figure 6. Plot of data splitting with training periods of 8 months (top), 6 months (middle) and 3 months (bottom)

### *2.4. Temporal Convolutional Neworks (TCN)*

In recent years, Temporal Convolutional Networks (TCN) have gained attention as a robust solution for analyzing sequential data by effectively capturing temporal patterns and long-term dependencies. The unique architecture of TCN incorporates several essential components, including causal and dilated convolution and residual connections, which enhance its effectiveness [23].

#### *2.4.1. Causal Convolutions*

One notable feature of TCN is its utilization of causal convolution, ensuring that the network's output at each time step relies solely on past inputs. This property is particularly beneficial for tasks involving sequential data, as it prevents information leakage from future time steps.

#### *2.4.2. Dilated Convolutions*

Wang et al. (2023) [23] explained that adding more than one causal convolutional layer can make the network more receptive, but it can also cause gradient problems in longer sequences. To tackle this, TCN introduces dilated convolutions, which progressively expand the network's receptive field. Dilated convolution samples the input of the upper layer at intervals, with the dilation rate growing exponentially based on 2. This method allows for a broader receptive field with fewer network layers. The computation formula for dilated convolution is represented as follows:

$$F(s) = (x *_{d} f(s) = \sum_{t=0}^{k-1} f(t)\ .\ x_{s-d\ .\ t} \qquad (1)$$

In this context, the rate of dilation is referred to as $d$, the size of the filter is denoted as $k$, and $x_{s-d\,.\,t}$ represents the convolution of the previous state. This approach effectively decreases network complexity while improving computational efficiency. Moreover, the architecture of dilated convolutions can be illustrated, as depicted in Figure 7 [24].

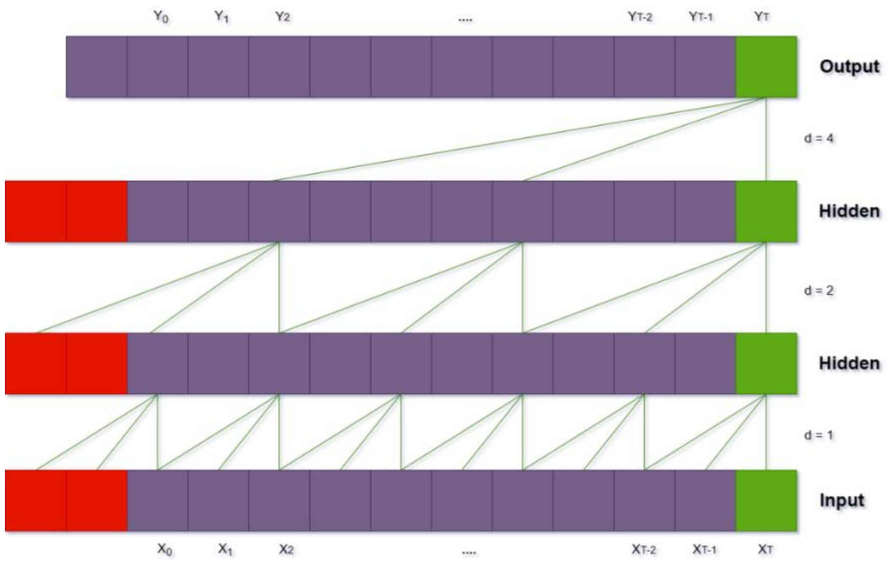


Figure 7. Architecture of dilated convolutions with $d$ = 1, 2, 4 and $k$ = 3

In this study, we employ the TCN machine learning model to design a water level forecasting system. Details of the TCN configuration are provided in Table 1.

Table 1. The configuration of TCN

| Model | Model Setting |
|---|---|
| TCN | Layer = 1 (5 hidden layer)<br>Batch size = 32<br>Epoch = 10000<br>Patient = 10<br>Activation = linear<br>Optimizer = adam(1e-3)<br>Loss = huber |

### 2.5. Peformance Metrics

To determine the model with the best forecasting accuracy, we utilize the coefficient of determination ($R^2$) and Root Mean Squared Error (RMSE) as performance metrics. The coefficient of determination ($R^2$), a commonly used quantitative metric for evaluating a model's predictive capability, ranges from 0 to 1 [10]. The formula for $R^2$ is as follows (2-4):

$$R^2 = 1 - \frac{RSS}{TSS}, \tag{2}$$

$$RSS = \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 , \tag{3}$$

$$TSS = \sum_{i=1}^{N} (y_i - (\frac{1}{N}\sum_{i=1}^{N} y_i))^2 \tag{4}$$

In Equation (2)-(4), RSS is Residual Sum of Squares, while TSS represents Total Sum of Squares. Here, $y_i$ denotes the individual observed value, $N$ represents the total number of data points, and $\hat{y}_i$ represents the predicted value [10].

The RMSE serves as a measure to assess the average error's magnitude. The formula for RMSE is as follows [25]:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \tag{5}$$

## 3. RESULT AND DISCUSSION

In this section, we conduct water level forecasting using data from the water level station monitoring facility in Surabaya, Indonesia. To optimize the model's performance, we divide the training data into several scenarios to assess their sensitivity. These scenarios consist of periods spanning 3 months (from September 11, 2023, to December 11, 2023), 6 months (from June 11, 2023, to December 11, 2023), and 8 months (from April 11, 2023, to December 11, 2023). Each scenario is then utilized as training data for the TCN model to generate 14-day forecasts (from December 11, 2023, to December 25, 2023). The best results can be seen in Table 2, which shows that using a training dataset that spans 8 months gives the highest coefficient of determination ($R^2$) and lowest RMSE values of 0.9903 and 0.0613, respectively.

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

| Length of Training Data | Coefficient of Determination ($R^2$) | RMSE |
|---|---|---|
| 3 Months | 0.7569 | 0.3065 |
| 6 Months | 0.9453 | 0.1454 |
| 8 Months | **0.9903** | **0.0613** |

Subsequently, employing an 8-month training dataset, we conducted forecasting for 1, 3, 7, and 14 days using TCN forecasts (from December 11, 2023, to December 25, 2023). Additionally, we employed other machine learning models, specifically Transformers and RNN, for comparison to determine their relative performance compared to TCN. The findings indicate that TCN outperforms Transformers and RNN in water level forecasting. These comparative results are presented in Table 3.

Table 3. Table result of 1 to 14 days of forecasting using various models

| Forecast | Transformers | | RNN | | TCN | |
|---|---|---|---|---|---|---|
| (Day) | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE |
| 1 | 0.9727 | 0.1135 | 0.9688 | 0.1213 | **0.9950** | **0.0487** |
| 3 | 0.9763 | 0.1112 | 0.9639 | 0.1372 | **0.9925** | **0.0626** |
| 7 | 0.9755 | 0.1109 | 0.9665 | 0.1296 | **0.9914** | **0.0656** |
| 14 | 0.9587 | 0.1263 | 0.9650 | 0.1162 | **0.9903** | **0.0613** |

Table 3 shows that TCN outperforms other models in forecasting accuracy, especially as the forecast duration shortens. Notably, TCN achieves its highest accuracy when predicting 1 day ahead, with impressive $R^2$ and RMSE values of 0.9950 and 0.0487, respectively. The forecasting accuracy of TCN becomes more evident when considering qualitative results. Figure 8 illustrates the 14-day forecasting outcomes from the Transformers, RNN, and TCN models. Notably, TCN consistently demonstrates accurate forecasting across all time points, unlike Transformers and RNN, which encounter challenges on specific days.

Figure 8 demonstrates the poor performance of the Transformers and RNN models in predicting data around peak points and valley points. Transformer and RNN models underestimate most data around peak points and valley points generally. Otherwise, the TCN model provides closer estimation results around peak and trough points.

One of the problems that usually occurs in coastal areas such as Surabaya is tidal flooding due to peak sea tides. Therefore, better predictions for data around peak points will provide very useful information for anticipating the impact of extreme tides. This is the contribution of this study, where the TCN model succeeds in estimating the peak point more closely than the Transformer and RNN models, which tend to underestimate points around the peak. Given that numerous other coastal locations in Indonesia are facing comparable water level issues, these results hold promise for predicting potential sea level rise over an extended period.

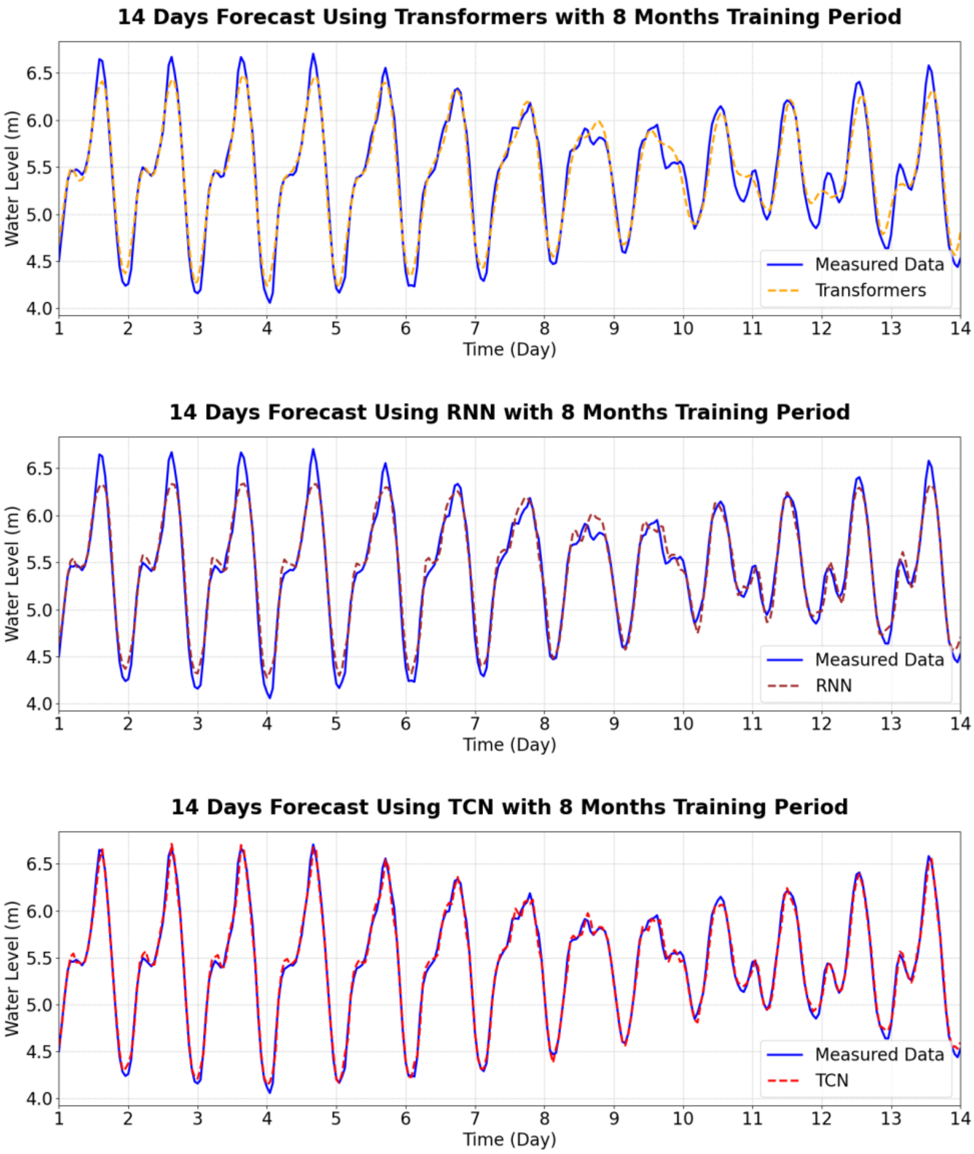


Figure 8. 14 days forecasting results from Transformers (top), RNN (middle) and TCN (bottom) using 8 months training period

## 4. CONCLUSION

In this study, we design a water level forecasting model using machine learning techniques, specifically TCN, and compare its performance with other models such as Transformers and RNN. Initially, we partitioned the training data into three scenarios spanning 3 months, 6 months, and 8 months to assess the sensitivity of the training data and optimize input for the TCN model. Each scenario serves as input for the TCN model to conduct 14-day forecasting. The results indicate that the 8-month training data scenario yields the most favorable outcomes. Subsequently, utilizing an 8-month training dataset, we conduct 1, 3, 7, and 14-day forecasting using TCN, Transformers, and RNN models. The results show that TCN consistently does better than the other models at all forecasting intervals. It is most accurate at 1-day forecasting, with an $R^2$ value of 0.9950 and an RMSE value of 0.0487. For future research, leveraging a larger dataset could enhance the validation of TCN's accuracy. Additionally, conducting comparisons with other machine learning models, such as XGBoost, could provide further insights into evaluating the TCN model's performance.

## ACKNOWLEDGEMENTS

This research was funded by Telkom University NO. 659/PNLT3/PPM/2023.

## REFERENCES


[1] M. E. Hauer *et al.*, "Sea-level rise and human migration," *Nat Rev Earth Environ*, vol. 1, no. 1, pp. 28–39, 2020, doi: 10.1038/s43017-019-0002-9.

[2] M. Taherkhani, S. Vitousek, P. L. Barnard, N. Frazer, T. R. Anderson, and C. H. Fletcher, "Sea-level rise exponentially increases coastal flood frequency," *Sci Rep*, vol. 10, no. 1, p. 6466, 2020, doi: 10.1038/s41598-020-62188-4.

[3] A. Cazenave, H. Palanisamy, and M. Ablain, "Contemporary sea level changes from satellite altimetry: What have we learned? What are the new challenges?," *Advances in Space Research*, vol. 62, no. 7, pp. 1639–1653, 2018, doi: https://doi.org/10.1016/j.asr.2018.07.017.

[4] R. S. Nerem, B. D. Beckley, J. T. Fasullo, B. D. Hamlington, D. Masters, and G. T. Mitchum, "Climate-change–driven accelerated sea-level rise detected in the altimeter era," *Proceedings of the National Academy of Sciences*, vol. 115, no. 9, pp. 2022–2025, Feb. 2018, doi: 10.1073/pnas.1717312115.

[5] N. A. Agustina, Supartono, and V. D. Prasita, "Rob Flood as impact of sea level rise around Kenjeran Beach Tourism Surabaya," *IOP Conf Ser Earth Environ Sci*, vol. 1273, no. 1, p. 012084, 2023, doi: 10.1088/1755-1315/1273/1/012084.

[6] D. Fitriana, M. P. Patria, and E. Kusratmoko, "Detection of Sea Level Rise Monitored from Surabaya Tidal Station Data from 2013 to 2021," *IOP Conf Ser Earth Environ Sci*, vol. 1111, no. 1, p. 012051, 2022, doi: 10.1088/1755-1315/1111/1/012051.

[7] G. Griggs, "Rising Seas in California — An Update on Sea-Level Rise Science," in *World Scientific Encyclopedia of Climate Change*, pp. 105–111. doi: 10.1142/9789811213960_0016.

[8] A.-L. Balogun and N. Adebisi, "Sea level prediction using ARIMA, SVR and LSTM neural network: assessing the impact of ensemble Ocean-Atmospheric processes on models' accuracy," *Geomatics, Natural Hazards and Risk*, vol. 12, no. 1, pp. 653–674, 2021, doi: 10.1080/19475705.2021.1887372.

[9] X. H. Le, H. Ho, G. Lee, and S. Jung, "Application of Long Short-Term Memory (LSTM) Neural Network for Flood Forecasting," *Water (Basel)*, vol. 11, p. 1387, Feb. 2019, doi: 10.3390/w11071387.

[10] 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.

[11] A. R. Amiri-Simkooei, S. Zaminpardaz, and M. A. Sharifi, "Extracting tidal frequencies using multivariate harmonic analysis of sea level height time series," *J Geod*, vol. 88, no. 10, pp. 975–988, 2014, doi: 10.1007/s00190-014-0737-5.

[12] S. Li, L. Liu, S. Cai, and G. Wang, "Tidal harmonic analysis and prediction with least-squares estimation and inaction method," *Estuar Coast Shelf Sci*, vol. 220, pp. 196–208, 2019, doi: https://doi.org/10.1016/j.ecss.2019.02.047.

[13] Y. M. L. C. Naiquan Zheng Hongzhou Chai and P. Chen, "Hourly sea level height forecast based on GNSS-IR by using ARIMA model," *Int J Remote Sens*, vol. 43, no. 9, pp. 3387–3411, 2022, doi: 10.1080/01431161.2022.2091965.

[14] R. Tulus, D. Adytia, N. Subasita, and D. Tarwidi, "Sea Level Prediction by Using Seasonal Autoregressive Integrated Moving Average Model, Case Study in Semarang, Indonesia," in *2020 8th International Conference on Information and Communication Technology (ICoICT)*, 2020, pp. 1–5. doi: 10.1109/ICoICT49345.2020.9166423.

[15] D. S. Wibowo, D. Adytia, and D. Saepudin, "Prediction of Tide level by using Holtz-Winters Exponential Smoothing: Case study in Cilacap Bay," in *2020 International Conference on Data Science and Its Applications (ICoDSA)*, 2020, pp. 1–5. doi: 10.1109/ICoDSA50139.2020.9212920.

[16] K. Ishida, G. Tsujimoto, A. Ercan, T. Tu, M. Kiyama, and M. Amagasaki, "Hourly-scale coastal sea level modeling in a changing climate using long short-term memory neural network," *Science of The Total Environment*, vol. 720, p. 137613, 2020, doi: https://doi.org/10.1016/j.scitotenv.2020.137613.

[17] M. Pan *et al.*, "Water level prediction model based on GRU and CNN," *Ieee Access*, vol. 8, pp. 60090–60100, 2020.

[18] C. H. Goay, N. S. Ahmad, and P. Goh, "Temporal convolutional networks for transient simulation of high-speed channels," *Alexandria Engineering Journal*, vol. 74, pp. 643–663, 2023, doi: https://doi.org/10.1016/j.aej.2023.05.059.

[19] Y. Wang *et al.*, "Short-Term Load Forecasting for Industrial Customers Based on TCN-LightGBM," *IEEE Transactions on Power Systems*, vol. 36, no. 3, pp. 1984–1997, 2021, doi: 10.1109/TPWRS.2020.3028133.

[20] L. Gong, M. Yu, S. Jiang, V. Cutsuridis, and S. Pearson, "Deep Learning Based Prediction on Greenhouse Crop Yield Combined TCN and RNN," *Sensors*, vol. 21, no. 13, 2021, doi: 10.3390/s21134537.

[21] P. Hewage *et al.*, "Temporal convolutional neural (TCN) network for an effective weather forecasting using time-series data from the local weather station," *Soft comput*, vol. 24, no. 21, pp. 16453–16482, 2020, doi: 10.1007/s00500-020-04954-0.

[22] P. Lara-Benítez, M. Carranza-García, J. M. Luna-Romera, and J. C. Riquelme, "Temporal Convolutional Networks Applied to Energy-Related Time Series Forecasting," *Applied Sciences*, vol. 10, no. 7, 2020, doi: 10.3390/app10072322.

[23] C. Zuo, J. Wang, M. Liu, S. Deng, and Q. Wang, "An Ensemble Framework for Short-Term Load Forecasting Based on TimesNet and TCN," *Energies (Basel)*, vol. 16, no. 14, 2023, doi: 10.3390/en16145330.

[24] S. Bai, J. Z. Kolter, and V. Koltun, "An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling." 2018.

[25] Y. F. Jian Zhao and Y. Mu, "Sea Level Prediction in the Yellow Sea From Satellite Altimetry With a Combined Least Squares-Neural Network Approach," *Marine Geodesy*, vol. 42, no. 4, pp. 344–366, 2019, doi: 10.1080/01490419.2019.1626306.