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Coastal Erosion Prediction at Oesapa Beach, Kupang City, Using Backpropagation and Fuzzy Time Series

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ABSTRACT

Coastal erosion is a significant environmental problem that threatens shoreline stability, coastal infrastructure, and community livelihoods. This study aims to predict coastal erosion at Oesapa Beach, Kupang City, by comparing the Backpropagation algorithm and Fuzzy Time Series (FTS) using three environmental variables: sea wave height, tidal fluctuations, and wind speed. Historical environmental data obtained from the Meteorology, Climatology, and Geophysics Agency (BMKG) of East Nusa Tenggara for the 2010–2016 period were processed and analyzed to develop the prediction models. The research involved data preparation, preprocessing, model training, testing, prediction, and performance evaluation using Mean Squared Error (MSE). The results demonstrate that Backpropagation achieved lower testing errors across all three environmental variables, with MSE values of 0.089607 for sea wave height, 0.075699 for tidal fluctuations, and 0.054443 for wind speed. In contrast, FTS produced MSE values of 69.3302, 2.426, and 4647.1802, respectively. The predicted coastal erosion value for 2020 was 0.52 m using Backpropagation and 2.02 m using FTS. These findings indicate that Backpropagation provided better predictive performance than FTS within the scope of the evaluated dataset. The comparison highlights the importance of selecting an appropriate forecasting method when modeling environmental variables associated with coastal erosion. Backpropagation is therefore identified as the more suitable method among the two approaches evaluated in this study for predicting coastal erosion at Oesapa Beach, Kupang City.

INTRODUCTION

Indonesia is an archipelagic and maritime country with an estimated coastline of approximately 95,181 km. Its extensive coastal areas provide important natural resources and support various community livelihoods and regional economic activities. However, these areas are also vulnerable to environmental problems, particularly coastal erosion. Continuous erosion can cause shoreline retreat, reduce coastal land, degrade coastal ecosystems, and threaten infrastructure and buildings located near the shoreline (Alnursa, 2022). Coastal erosion is influenced by various natural and anthropogenic processes, including wave activity, sediment transport, sea-level variation, and changes in coastal environmental conditions (Hastuti et al., 2024).

Kupang City, the capital of East Nusa Tenggara Province, has a coastal environment directly connected to Kupang Bay. Its coastal areas are utilized for residential settlements, fisheries, tourism, trade, and other community activities (Jerobisonif et al., 2023). Oesapa Beach is one of the coastal areas experiencing substantial human activity and therefore has considerable social and economic importance. Changes in the environmental condition of Oesapa Beach may affect coastal land, public facilities, buildings, and community activities located along the shoreline (Boikh et al., 2023). Consequently, understanding the development of coastal erosion in this area is important for supporting appropriate coastal management and mitigation efforts.

The coastal erosion process at Oesapa Beach involves several environmental factors that vary over time. Tidal conditions, wind velocity, and wave height are important parameters that describe the surrounding marine environment and may contribute to shoreline changes (N. Nawa et al., 2025). These variables can interact with one another and influence wave energy, sediment movement, and the physical stability of the shoreline. Therefore, analyzing coastal erosion using multiple environmental variables may provide a more comprehensive representation of the processes involved than relying on a single parameter (Ibrahim et al., 2023). Historical observations of these variables can consequently provide valuable information for identifying patterns associated with coastal erosion.

The interaction among environmental variables and coastal erosion may involve complex and nonlinear relationships. Therefore, an analytical approach capable of processing historical data and recognizing relationships

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among multiple variables is required (Tran & Nguyen, 2025). Data-driven modeling provides an alternative approach for addressing such problems by extracting patterns from historical observations and using them to estimate future conditions (Adusumilli et al., 2024). One suitable approach is Artificial Neural Networks (ANN) using the Backpropagation algorithm, which can learn relationships between input and output variables through an iterative process of weight adjustment. The learning mechanism of Backpropagation allows the model to represent complex patterns and nonlinear relationships within environmental datasets (Bangsawan et al., 2024).

Based on these considerations, this study focuses on predicting coastal erosion at Oesapa Beach, Kupang City, using Backpropagation and Fuzzy Time Series approaches. The prediction process utilizes historical data on tidal conditions, wind velocity, and wave height as environmental variables associated with coastal erosion. The Backpropagation and Fuzzy Time Series methods are applied to identify patterns and temporal relationships within the historical data and to generate predictions of future coastal erosion conditions. Furthermore, this study aims to compare the performance of the two prediction methods and determine which approach provides more accurate and reliable results in predicting coastal erosion at Oesapa Beach. The performance comparison is conducted based on the prediction results and the corresponding error values obtained from each method. The findings are expected to provide useful scientific information for understanding coastal erosion dynamics at Oesapa Beach and to support coastal management, mitigation planning, and the protection of coastal communities and infrastructure.

LITERATURE REVIEW

Artificial Intelligence

Artificial Intelligence (AI) is an area of computer science that focuses on developing computational technologies capable of carrying out tasks that generally involve human cognitive abilities. AI-based systems are developed to process and interpret information, recognize patterns, generate decisions, and solve problems through computational techniques and algorithmic procedures. By learning or deriving patterns from available data, these systems can produce outputs or solutions for specific problems. AI has been implemented through various computational approaches, including Artificial Neural Networks (ANN), fuzzy logic, and evolutionary algorithms, each of which can be utilized to address problems with different levels of complexity (Avrilia et al., 2026).

Neural Network

An Artificial Neural Network (ANN) is an AI-based computational model designed by adopting concepts from the structure and information-processing behavior of biological neural systems. The model is composed of interconnected processing elements known as neurons, which collectively receive, process, and transmit information from input to output. Through the connections among neurons, an ANN can learn patterns contained in a dataset and establish relationships between input variables and their corresponding outputs. Unlike biological neural systems, ANN represents these processes through mathematical operations implemented in computer programs. During the learning process, the weights associated with connections between neurons are adjusted according to the information contained in the training data and the desired target output. Repeated adjustment of these weights enables the network to improve its ability to represent patterns within the data. Because of this learning capability, ANN has been widely applied to various computational tasks, including classification, pattern recognition, prediction, and modeling of complex relationships between variables (Pramesti & Suhendro, 2024).

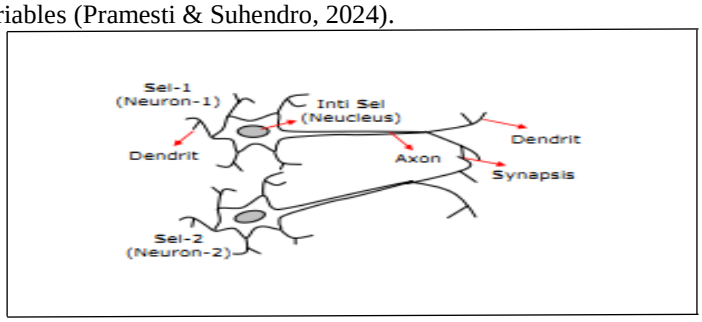


Figure 1. Structure of the Human Nervous System

The figure above presents a representation of the human nervous system and its neural organization. The fundamental concept of an Artificial Neural Network (ANN) is inspired by the way biological neurons receive, process, and transmit information. In an artificial network, individual neurons are interconnected so that information can be transferred from one processing unit to another through weighted connections. The output generated by one neuron can subsequently become an input for another connected neuron, allowing information to propagate throughout the network (Pramesti & Suhendro, 2024). A biological neuron is generally composed of three major structural parts: dendrites, the

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soma (cell body), and the axon. Dendrites receive incoming signals, while the soma processes the received information and the axon transmits the resulting signal to other neurons or cells. Communication between neurons occurs through electrochemical processes involving synapses. When the accumulated incoming signal reaches a sufficient threshold, the neuron produces an electrical impulse that can be transmitted through the axon. The characteristics and frequency of these signals may differ depending on the activity and condition of individual neurons.

Another important characteristic of biological neural systems is their ability to maintain functionality despite disturbances or partial damage. The human brain can recognize patterns even when incoming information differs from previously learned patterns. In addition, the overall neural system may continue to function when some neurons are impaired or no longer operate optimally. Other neurons can potentially adapt and compensate for the affected functions through learning and neural reorganization (Timorremboko & Karya, 2020). These characteristics have provided an important conceptual basis for the development of Artificial Neural Networks, particularly in terms of their ability to learn from data, recognize patterns, and adapt their internal representations according to the information provided during the learning process. Similar to biological neural systems, ANN models consist of interconnected processing units that cooperate to transform input information into an appropriate output. In general, an Artificial Neural Network is constructed from three fundamental components: network architecture, learning algorithm, and activation function. The architecture determines how neurons are organized and interconnected, the learning algorithm controls how the connection weights are adjusted during the training process, and the activation function determines the output response of each neuron based on its received input. These three components work together to determine how an ANN processes information and learns patterns from a given dataset.

Activation Functions

Activation functions are essential components of an Artificial Neural Network because they determine how the information received by a neuron is transformed into an output value. By applying an activation function to the weighted input received by a neuron, the network can control the response generated at each processing unit. The choice of activation function also affects the way information is processed and propagated between neurons during the learning process (Pamungkas et al., 2022). Several activation functions can be employed in Artificial Neural Network models depending on the characteristics of the problem and the desired output. Among the functions commonly used in neural network computation are the Binary Sigmoid Function, which produces output values within a specific positive range; the Bipolar Sigmoid Function, which provides output values extending from negative to positive values; and the Linear (Identity) Function, in which the output maintains a direct relationship with the input. These functions provide different transformation characteristics and can therefore be selected according to the requirements of the neural network model.

Backpropagation Algorithm

The Backpropagation algorithm is a supervised learning technique widely used in multilayer neural networks to train the model by modifying the weights of connections between neurons. Its primary purpose is to minimize the difference between the output generated by the network and the expected target value. Through an iterative learning process, the algorithm adjusts the connection weights, including those connecting the hidden layers, so that the network can gradually learn the relationship between input patterns and their corresponding outputs.

The learning mechanism of Backpropagation can generally be divided into two sequential processes: forward propagation and backward propagation. In forward propagation, the input data are passed through the network layer by layer, beginning at the input layer and continuing toward the output layer. At each neuron, the incoming values are combined with their corresponding weights and processed through an activation function. The final value generated at the output layer is then evaluated against the target value to obtain the associated error.

The error obtained from the output layer becomes the basis for the backward propagation process. In this stage, the error information is transmitted in the reverse direction through the network to determine how the connection weights should be modified. The updated weights are intended to reduce the difference between the predicted and target values during subsequent iterations. This forward-and-backward learning cycle continues repeatedly until a specified stopping condition is satisfied or the resulting error reaches an acceptable level. A differentiable activation function, such as the sigmoid function, can be used during forward propagation because its derivative is required in calculating the weight adjustments during the learning process (Ulumando, 2025).

$$y = F(X) = \frac{1}{1+e^{-\sigma X}} \quad (1)$$

$$f'(X) = \sigma f(X)[1 - f(X)] \quad (2)$$

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Fuzzy Time Series

Fuzzy Time Series (FTS) is a forecasting method that integrates the principles of fuzzy set theory with time-series analysis to model and predict data that may contain uncertainty, imprecision, or gradual changes over time. The method was initially introduced by Song and Chissom and has subsequently been developed and applied in various forecasting problems. Unlike conventional time-series approaches that generally use precise numerical observations, FTS provides a framework for representing data using fuzzy concepts, making it suitable for situations in which observations may exhibit uncertain or linguistic characteristics (Pattanayak et al., 2020).

The implementation of Fuzzy Time Series generally begins by defining a universal set (U) that covers the range of observed data. This universal set is then divided into several intervals, which are represented by corresponding fuzzy sets. The historical observations are subsequently transformed or fuzzified according to their membership in these fuzzy sets. The resulting fuzzy relationships are used to construct a forecasting model, which can then generate predicted values for future periods. In this study, the universal set is denoted by U and can be formulated as follows:

$$U = \{ u_1, u_2, \dots \dots u_n \} \tag{3}$$

Where $u_1, u_2, \dots \dots u_n$ represent the elements contained in the universal set and n denotes the total number of elements. A fuzzy set A_i defined on the universal set U can then be represented as:

$$A_i = \frac{fA_i(u_1)}{u_1} + \frac{fA_i(u_2)}{u_2} + \cdots + \frac{fA_i(u_n)}{u_n} \tag{4}$$

Where fA_i represents the membership function of fuzzy set A_i. The membership function is defined as:

$$fA_i : U \rightarrow [0,1] \tag{5}$$

The value $fA_i\ (u_j)$ represents the degree of membership of element u_j in fuzzy set A_i. Therefore:

$$0 \leq fA_i\ (u_j) \leq 1 \tag{6}$$

A membership value close to 1 indicates that an observation has a strong association with a particular fuzzy set, whereas a value close to 0 indicates a weak association.

Coastal Erosion

Coastal erosion is a natural geomorphological process characterized by the gradual loss of material along the shoreline due to marine forces, particularly wave action and coastal currents. In a broader context, erosion refers to the detachment and movement of soil or other surface materials from one location to another through natural agents such as water, wind, or other environmental processes. In coastal areas, this process may lead to the removal, transportation, and subsequent deposition of sediments in different locations. Furthermore, environmental changes associated with climate change, including rising sea levels, may increase the exposure of coastal areas to erosion and contribute to changes in shoreline conditions (Ibrahim et al., 2023).

One of the main indicators of coastal erosion is the landward movement of the shoreline relative to its previous position. Shoreline changes may occur through two opposing but interconnected processes, namely erosion and accretion. Erosion occurs when coastal materials are removed, whereas accretion takes place when transported sediments accumulate in another part of the coast. The balance between these processes is influenced by coastal currents, sediment transport, and the availability of sediment from sources such as rivers, marine environments, and existing beach materials. Persistent changes in sediment distribution can disturb this balance and subsequently produce variations in shoreline position and coastal morphology (Putra et al., 2026).

The occurrence and intensity of coastal erosion are also associated with several natural environmental factors. In this study, wave height, wind velocity, and tidal fluctuations are considered important variables because of their potential influence on coastal processes. Increased wind velocity can contribute to the generation of higher and more energetic waves, which may enhance the transport and removal of coastal sediments. Meanwhile, changes in tidal levels modify the extent of the shoreline exposed to marine forces. The combined interaction of waves, wind, tides, and sediment processes can therefore influence the development and spatial characteristics of coastal erosion over time.

Profile of Oesapa Urban Village, Kupang City

Oesapa Urban Village is one of the administrative areas within Kelapa Lima District, Kupang City, East Nusa Tenggara Province (Djati et al., 2023). A portion of the area is located along the coastal zone of Kupang Bay, giving

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Oesapa a strategically important geographical position (Mendrofa & Davinsy, 2024). The area is also traversed by Timor Raya Road, a major national road that serves as an important transportation corridor connecting Kupang with other regions and functioning as one of the main access routes toward the border area with the neighboring country of Timor-Leste (Bella et al., 2023). The location of Oesapa Urban Village and its surrounding area is presented in Figure 2 (Wikimapia, 2016).

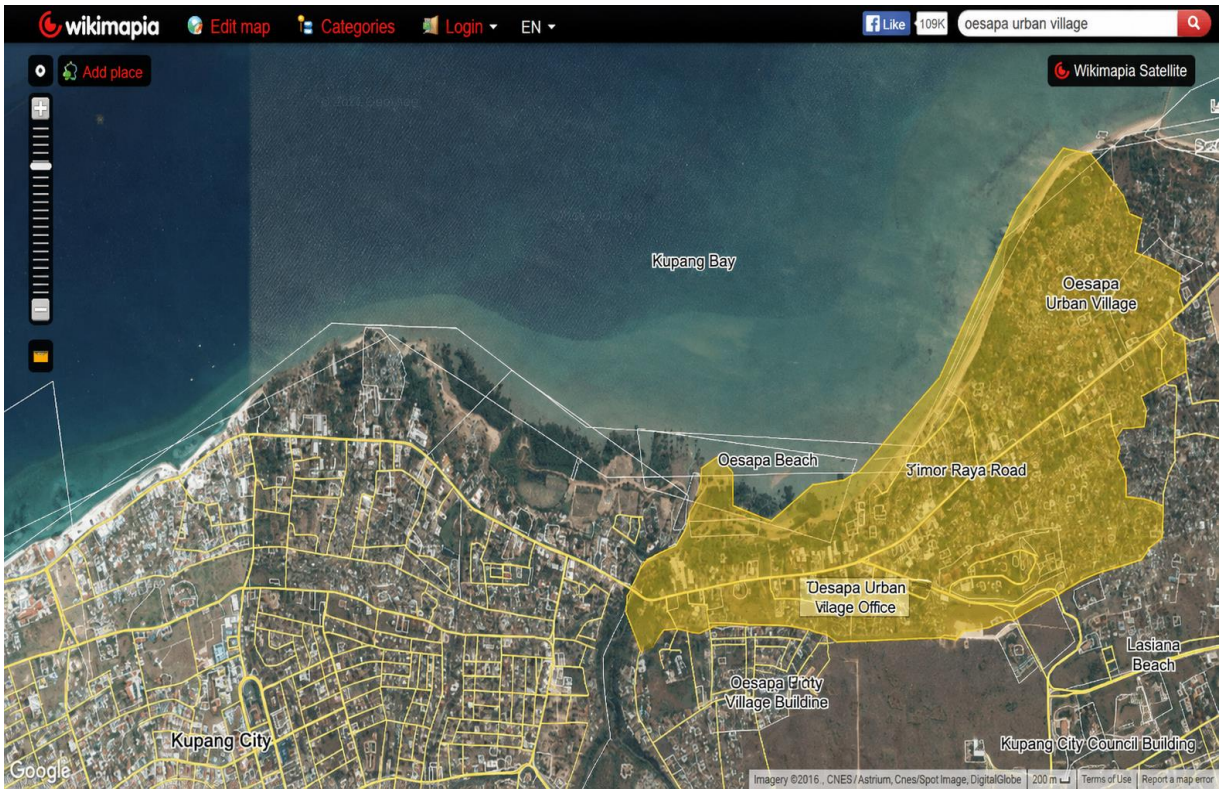


Figure 2. Map of the Oesapa Urban Village Area, Kupang City.

Based on the highlighted area in Figure 2, Oesapa Urban Village covers a total area of approximately 4.37 km². The community of Oesapa is characterized by considerable diversity in terms of ethnicity, cultural background, language, religious affiliation, and social status. This diverse social composition contributes to the complexity of community life and creates various social conditions and challenges. At the same time, such diversity represents an important social asset that can support the development and advancement of Oesapa Urban Village as part of the administrative area of Kupang City (Mendrofa & Davinsy, 2024).

Oesapa Beach Area, Kupang City

The coastal area of Oesapa Beach, Kupang City, is considered vulnerable to coastal erosion, which may pose risks to nearby residential areas and the livelihoods of communities that depend on coastal resources. Continued shoreline retreat can reduce the availability of coastal land and restrict activities that have traditionally been carried out along the shoreline. In addition to its potential effects on settlements and local livelihoods, coastal erosion may also influence the tourism sector. Damage to the beach environment and the degradation of coastal landscapes can reduce the attractiveness of the area as a tourist destination and may consequently lead to a decline in tourist visits (Djati et al., 2023).

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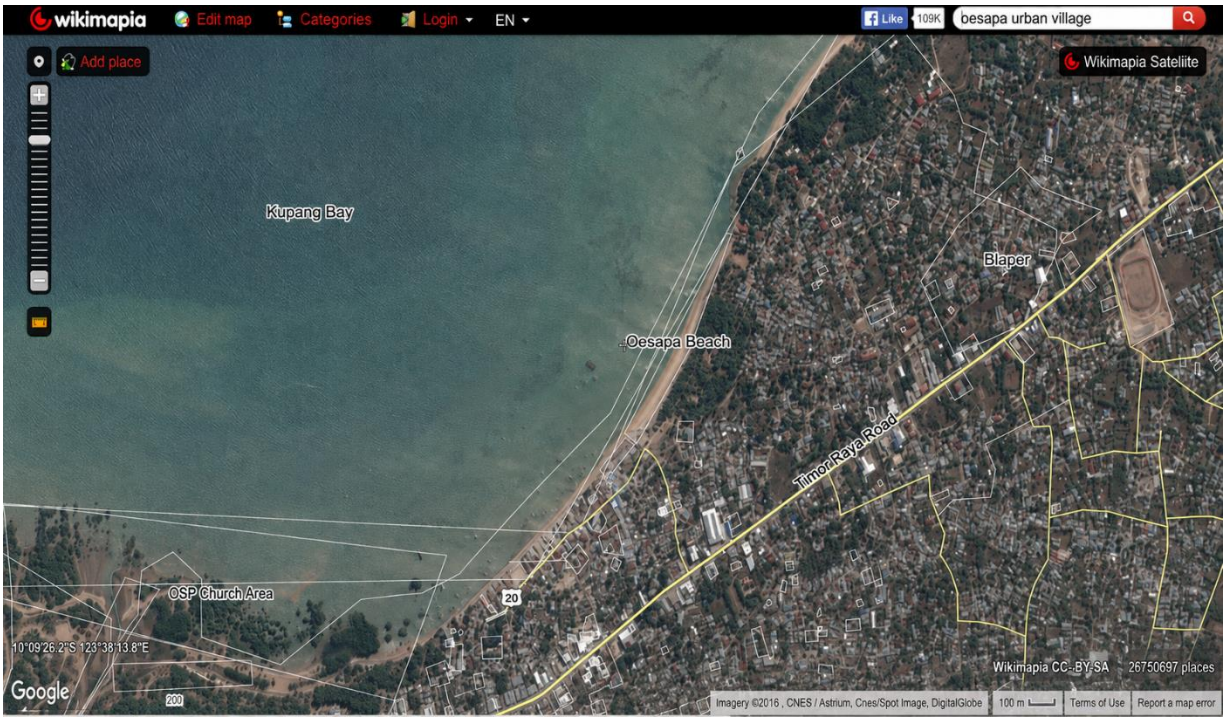


Figure 3. Map of the Oesapa Beach area, Kupang City

The shoreline of Oesapa Beach in Kupang City extends for approximately 2.77 km, with a coastal slope of approximately 30°, based on the map data and the results of field observations and interviews (Map, 2016; Observation and Interview Results). The coastal area is surrounded by residential settlements, hotel facilities, and mangrove vegetation, some of which have experienced environmental degradation (Wikimapia, 2016). In particular, fishing communities are located on the coastal land and in close proximity to the Oesapa shoreline, making them potentially vulnerable to changes in coastal conditions. Considering the proximity of residential areas and economic activities to the shoreline, Oesapa Beach requires comprehensive coastal management, particularly in sections that are considered vulnerable to coastal erosion. Appropriate assessment and preventive measures are necessary to minimize the potential impacts of shoreline retreat and reduce the risk of further coastal degradation in the future. Such efforts are also important for maintaining the sustainability of coastal resources and protecting communities and activities that depend on the Oesapa coastal environment (Djati et al., 2023) (Mendrofa & Davinsy, 2024).

METHOD

Data Collection and Research Equipment

The data collection stage was conducted to obtain the information required to analyze coastal erosion at Oesapa Beach, Kupang City, and to support the development of the prediction model. Three complementary approaches were employed, namely literature review, interviews, and field observation. The literature review involved examining scientific articles, books, and other relevant references concerning coastal erosion, environmental factors influencing shoreline dynamics, Artificial Neural Networks, and the Backpropagation algorithm. Interviews were conducted at the Meteorology, Climatology, and Geophysical Agency (BMKG) of East Nusa Tenggara Province to obtain information regarding the availability and characteristics of environmental data required for the research. Meanwhile, field observations were carried out directly at Oesapa Beach to examine the physical characteristics of the coastal area and obtain contextual information related to coastal erosion and its surrounding environmental conditions.

The research also required appropriate hardware and software to support data preparation, processing, model development, training, testing, and evaluation. The primary hardware used was a laptop equipped with an Intel Core i3-2330M processor operating at 2.20 GHz, 2 GB DDR3 RAM, a 32-bit operating system, a 500 GB hard disk, and an NVIDIA GeForce GT 520M graphics processor. These resources were used to perform the computational processes required throughout the research. The use of the available hardware was adjusted to the computational requirements of the Backpropagation-based prediction process.

For the software environment, the research used Windows 7 as the operating system and MATLAB R2014a as the primary computational platform. MATLAB was utilized to support the processing and preparation of the

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environmental datasets, implementation of the Backpropagation algorithm, model training and testing, and evaluation of the resulting prediction model. The combination of the data collection methods and computational resources provided the necessary foundation for conducting the subsequent stages of the research, particularly the development and evaluation of the coastal erosion prediction model at Oesapa Beach.

Research Flowchart

The research flowchart presents the overall sequence of activities undertaken in this study, from the initial identification of the coastal erosion problem at Oesapa Beach to the final interpretation of the research findings. The research process begins with problem identification and data collection, followed by data preparation and preprocessing. The relevant environmental variables are then determined and prepared for use in the prediction model. These stages provide the foundation for the subsequent development and implementation of the Backpropagation model.

The study focuses on three main environmental variables, namely tidal fluctuations, wind speed, and sea wave height. Historical observations of these variables are processed through the required preprocessing stages before being incorporated into the model. The prepared data are subsequently used during the training and testing processes to enable the Backpropagation network to learn patterns contained within the historical observations and generate the corresponding prediction results.

Following the training and testing stages, the performance of the developed model is evaluated using the appropriate evaluation criteria. The resulting outputs are then analyzed and interpreted to determine the model's ability to represent the relationship between the selected environmental factors and coastal erosion conditions. Overall, the research flow is designed to produce a coastal erosion prediction model for Oesapa Beach, Kupang City, while providing an analytical basis for understanding the contribution of tidal conditions, wind speed, and wave height to coastal erosion.

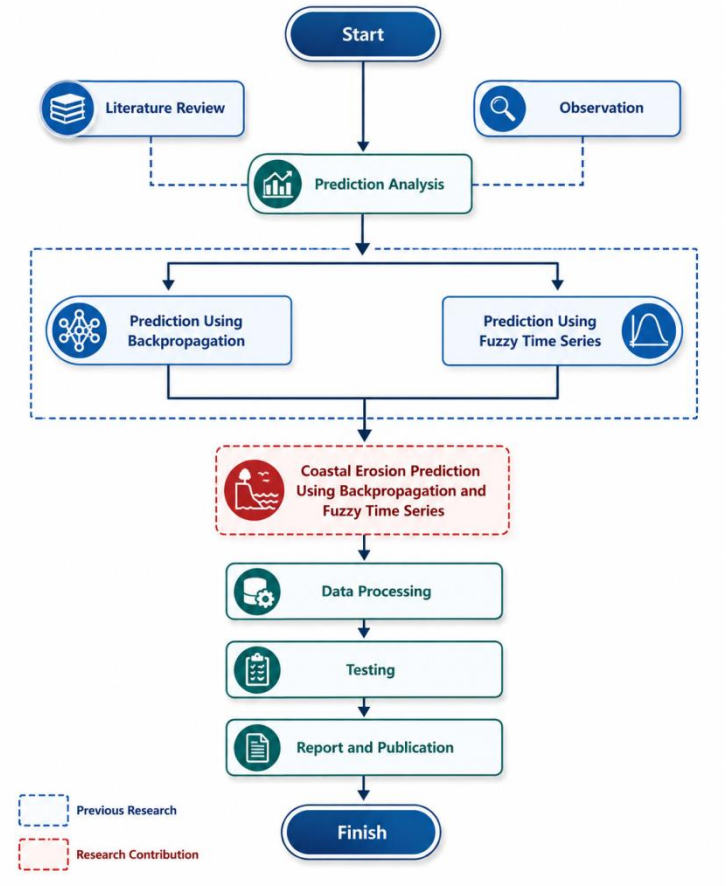


Figure 4. Research Process Flowchart

Figure 4 illustrates the research workflow used to predict coastal erosion at Oesapa Beach, Kupang City. The process begins with a literature review and field observation, which provide the theoretical background and contextual

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information for the study. The collected environmental data are then analyzed using two forecasting approaches: Backpropagation and Fuzzy Time Series. The prediction results are processed and tested to evaluate model performance. The blue dashed boundary represents the previous research process, whereas the red dashed boundary highlights the main contribution of the present study, namely the comparative application of the two methods for coastal erosion prediction. This workflow provides a structured basis for comparing the resulting predictions and evaluating the performance of both approaches.

The flowchart illustrates the overall research procedure, beginning with the literature review and field observation, which provide the theoretical and empirical foundations of the study. The process then proceeds to prediction analysis, where two approaches, Backpropagation and Fuzzy Time Series, are applied to the available environmental data. The results from both approaches are used to develop coastal erosion predictions, followed by data processing and testing to assess the reliability of the prediction results. The final stages involve compiling the findings into a research report and publication, with the blue-dashed section representing the previous research process and the red-dashed section highlighting the main contribution of the present study.

RESULT

This section discusses the processing and assessment of three environmental parameters considered relevant to coastal erosion at Oesapa Beach, Kupang City, namely sea wave height, tidal fluctuations, and wind speed. The dataset was obtained from the Meteorology, Climatology, and Geophysics Agency (BMKG) of East Nusa Tenggara and covers observations from 2010 to 2016 (BMKG, 2016). The collected observations were processed to examine the characteristics and patterns of the selected environmental variables as a basis for coastal erosion prediction. The Backpropagation algorithm was subsequently implemented to learn patterns contained in the historical observations and generate predictions. The resulting model was evaluated using prediction error and accuracy measures to assess its performance.

Data Presentation

The data preparation process began with the compilation of three environmental variables, consisting of sea wave height, tidal fluctuations, and wind speed. These variables were selected because they represent important environmental conditions associated with coastal dynamics at Oesapa Beach. The data were obtained from the Meteorology, Climatology, and Geophysics Agency (BMKG) of East Nusa Tenggara and initially consisted of daily observations.

To make the dataset more suitable for the prediction process, the daily observations were transformed into monthly data by calculating the average value for each month. The resulting monthly averages were then arranged chronologically according to their respective years and months. This dataset served as the basis for the subsequent preprocessing, normalization, training, testing, and prediction stages using the Backpropagation method.

Backpropagation-Based Testing

The data processing and testing procedure using the Backpropagation algorithm was conducted separately for each of the three environmental variables: sea wave height, tidal fluctuations, and wind speed. The processing of each variable followed a consistent sequence to ensure that the resulting data could be appropriately utilized by the neural network. The procedure began with the preparation of historical observations, followed by normalization to convert the original measurements into a numerical range suitable for neural network computation.

1. Sea Wave Height Testing

The analysis of sea wave height began with the preparation of historical observations collected over the study period. The monthly average sea wave height data used as the basis for the Backpropagation analysis are presented in Table 1. The table summarizes the average wave height recorded for each month from 2010 to 2016, providing an overview of the temporal variation in sea wave conditions during the observation period. These data were subsequently used in the preprocessing and normalization stages before being incorporated into the Backpropagation model.

Table 1. Monthly Average Sea Wave Height, 2010–2016

No.	Month	2010	2011	2012	2013	2014	2015	2016
1	January	2.6 m	2.7 m	2.5 m	3.6 m	2.8 m	3.1 m	1.8 m
2	February	1.8 m	2.5 m	1.8 m	2.5 m	2.4 m	2.0 m	2.4 m
3	March	1.4 m	1.8 m	2.5 m	2.0 m	2.5 m	1.9 m	1.7 m
4	April	1.5 m	1.6 m	2.2 m	2.1 m	2.2 m	2.2 m	1.7 m
5	May	2.1 m	2.1 m	3.6 m	2.5 m	2.6 m	3.0 m	3.0 m
6	June	2.7 m	1.7 m	3.2 m	3.3 m	3.7 m	3.6 m	1.9 m

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7	July	1.7 m	1.8 m	2.7 m	2.8 m	2.9 m	2.9 m	2.9 m
8	August	1.7 m	1.8 m	2.9 m	3.0 m	2.9 m	2.9 m	2.1 m
9	September	1.8 m	1.6 m	2.0 m	2.1 m	2.3 m	2.5 m	2.2 m
10	October	1.4 m	1.6 m	1.7 m	1.8 m	2.0 m	2.1 m	3.6 m
11	November	1.5 m	1.8 m	1.8 m	1.9 m	2.0 m	2.1 m	1.9 m
12	December	1.8 m	1.9 m	3.0 m	2.8 m	3.0 m	2.9 m	2.6 m
	Highest	**2.7 m**	**2.7 m**	**3.6 m**	**3.6 m**	**3.7 m**	**3.6 m**	**3.6 m**
	Lowest	**1.4 m**	**1.6 m**	**1.7 m**	**1.8 m**	**2.0 m**	**1.9 m**	**1.7 m**
	Average	**1.8 m**	**1.9 m**	**2.4 m**	**2.5 m**	**2.6 m**	**2.6 m**	**2.4 m**

Source: BMKG East Nusa Tenggara.

Following the presentation of the original wave height data in Table 1, the next stage involved transforming the observations through normalization. This process was performed to place the data within a consistent numerical range suitable for processing by the Backpropagation neural network. The normalization procedure was applied to all monthly observations using the following equation:

$$X'=(0,8(X-b)/(a-b))+0,1 \quad (7)$$

The normalization procedure was applied to the monthly sea wave height observations presented in Table 1. By applying the normalization equation, the original wave height values were transformed into normalized values within a consistent numerical range. This transformation was performed to ensure that the data were appropriately scaled and suitable for subsequent processing by the Backpropagation neural network. The results of the normalization process are presented in Figure 5. The figure illustrates the transformed wave height data after the normalization procedure was applied to the observations from 2010 to 2016. These normalized values were subsequently used as input data for the training and testing stages of the Backpropagation model.

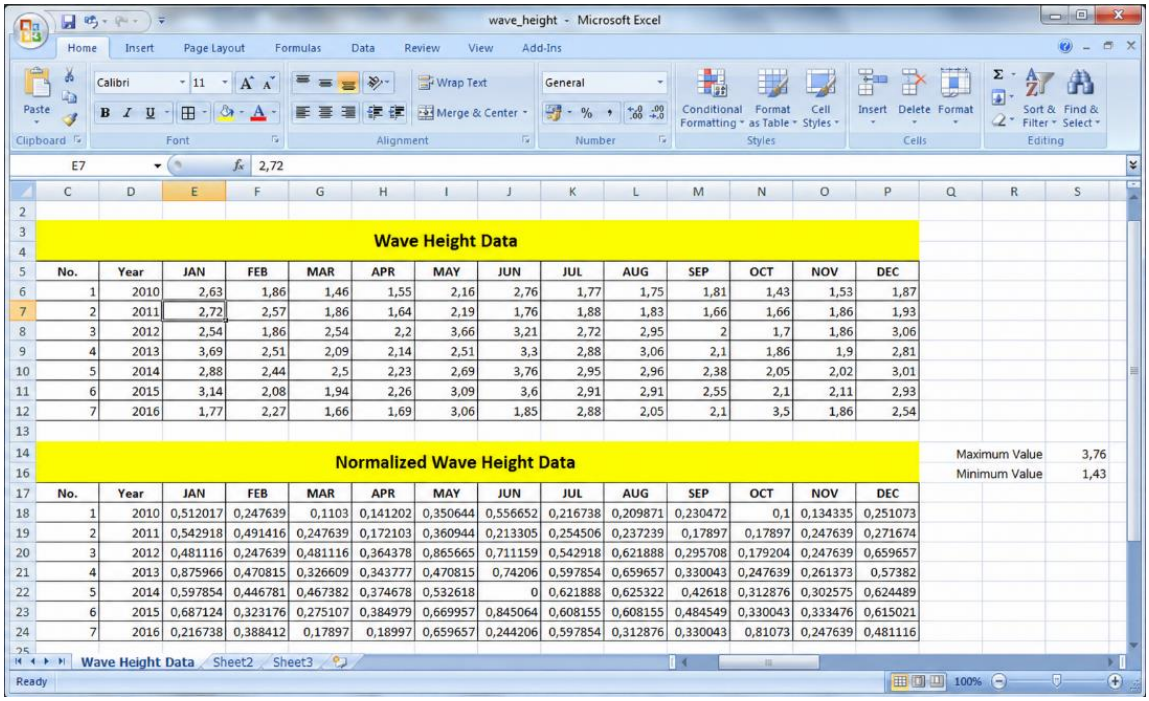


Figure 5. Wave height normalization results using backpropagation

Figure 5 presents the original and normalized sea wave height datasets used in this study for the period 2010–2016. The upper section contains the monthly average wave height observations, while the lower section shows the corresponding values after normalization. Based on the original observations, the maximum wave height was 3.76 m, whereas the minimum value was 1.43 m. The normalization process transformed the original data into a standardized numerical range, producing values that are more suitable for computational processing. The resulting normalized dataset serves as the basis for the subsequent Backpropagation training process. Following the normalization stage, the

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normalized sea wave height data were organized into sequential input patterns for the Backpropagation training process. The historical observations were arranged so that a series of previous monthly values could be used as input to predict the value of the subsequent month. During training, the Backpropagation network learns the relationship between the input patterns and their corresponding target values by continuously adjusting the connection weights between neurons. This iterative process is performed to minimize the difference between the network output and the target value. The training results are subsequently used as the basis for evaluating the model's capability to predict sea wave height in the next stage.

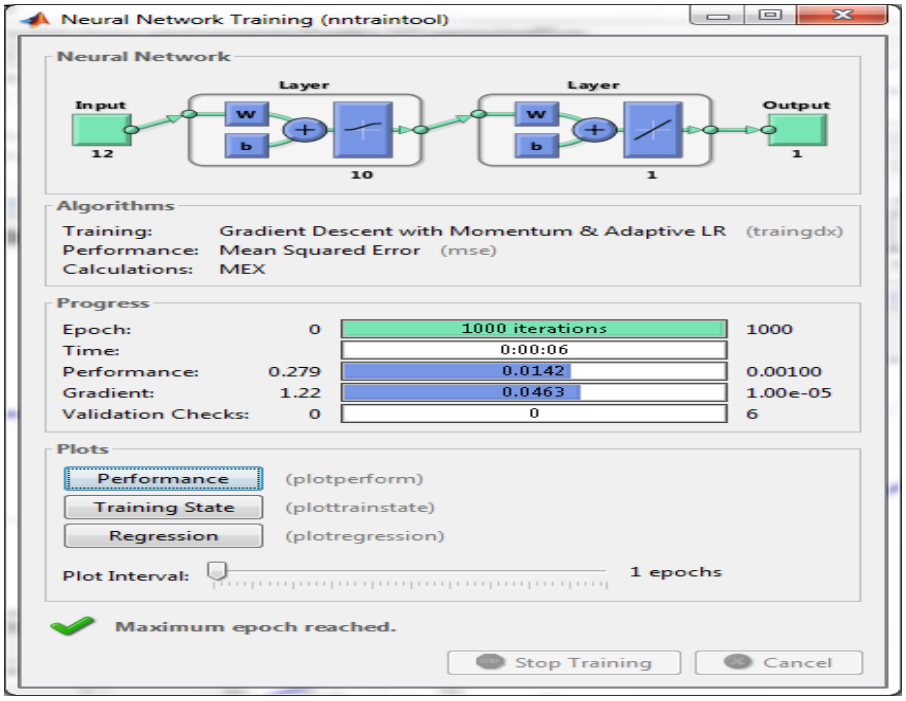


Figure 6. Neural network training for wave height using backpropagation

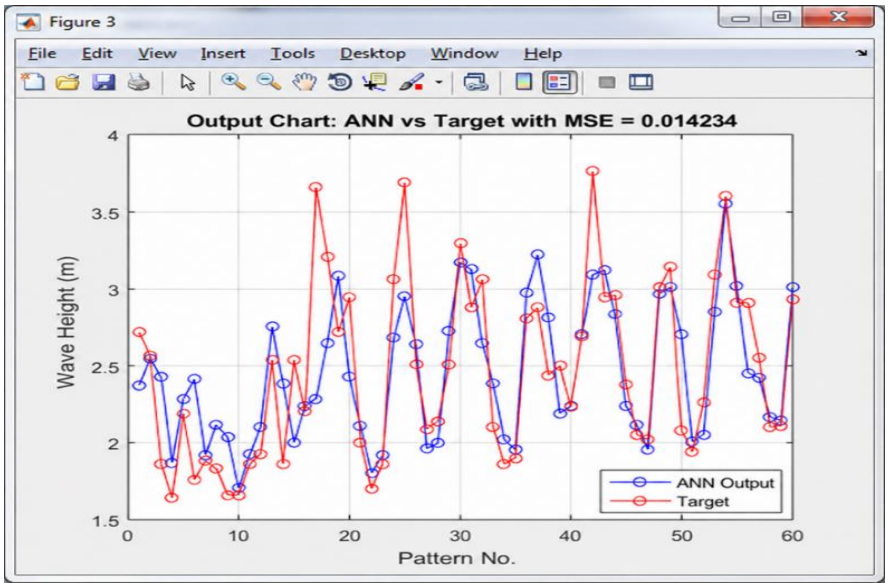


Figure 7. Wave Height Training Output Graph Using Backpropagation

Figure 6 illustrates the training configuration of the neural network for sea wave height prediction using the Backpropagation algorithm. The network consists of 12 input neurons, 10 neurons in the hidden layer, and 1 output neuron. The training process employs Gradient Descent with Momentum and Adaptive Learning Rate, while the model

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performance is evaluated using Mean Squared Error (MSE). The training process reaches the maximum of 1,000 iterations, with the displayed performance reaching approximately 0.0142. The resulting training output is presented in Figure 7, which compares the network output with the target values for 60 input patterns. As shown in the graph, the predicted output generally follows the fluctuations of the target data, although differences can still be observed at several patterns. The resulting MSE of 0.014234 indicates the error obtained during the training process and provides an initial indication of the model's ability to learn the pattern of sea wave height data.

After the training process has been completed, the trained Backpropagation network is subsequently used in the testing stage. The testing process is intended to evaluate whether the network that has learned the patterns from the training data can produce satisfactory outputs when applied to previously prepared testing data. The predicted values are compared with the corresponding actual sea wave height observations, and the resulting error is calculated to assess model performance. Following the testing stage, the trained model is then utilized to generate predictions of sea wave height for the specified future period. The results of the testing and the subsequent Sea Wave Height Prediction Using Backpropagation are presented in the following figures and tables.

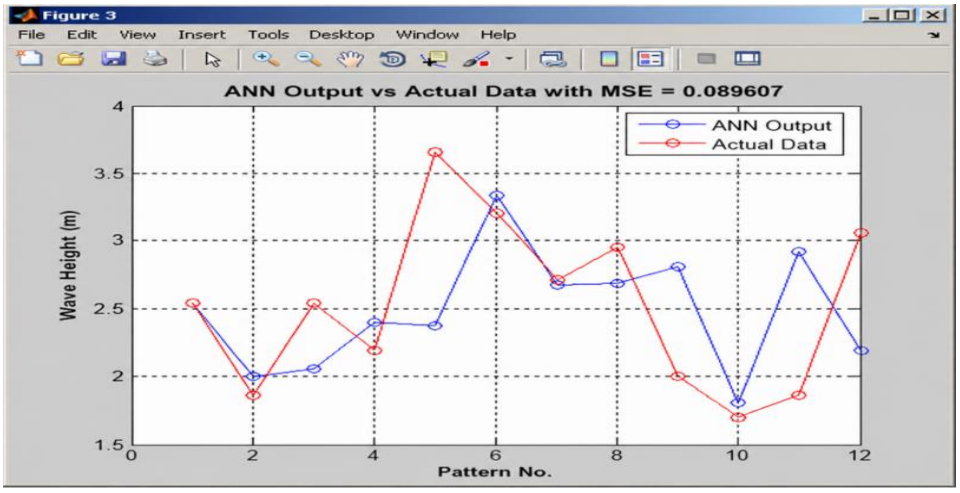


Figure 8. Output graph of wave height testing using backpropagation

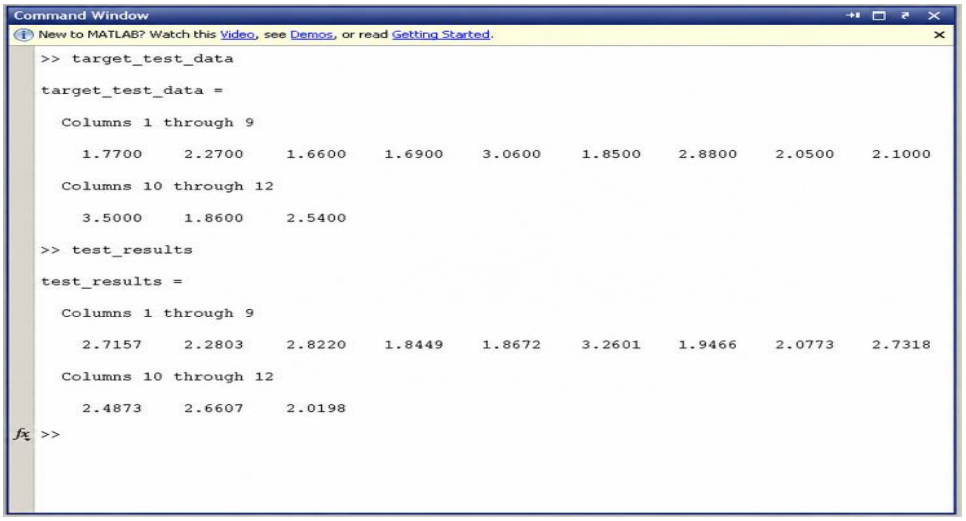


Figure 9. Comparison of actual data and test data for wave height using backpropagation.

Figure 8 presents the testing results of the sea wave height model using the Backpropagation algorithm, in which the network output is compared with the actual target values for 12 testing patterns. The graph shows that the predicted values generally follow the fluctuation pattern of the observed data, although differences remain at several patterns, particularly where the actual wave height changes considerably. The testing process produces an MSE value of 0.089607, indicating the average squared error between the predicted and actual wave height values. The numerical results shown in Figure 9 further provide the actual testing data and the corresponding outputs generated by the trained

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neural network. The comparison demonstrates that the model is able to reproduce the general pattern of the observed wave height data, although some deviations occur between the predicted and actual values. After the testing stage, the trained Backpropagation model was subsequently utilized to generate future sea wave height predictions. The prediction process was performed by providing the model with the corresponding input patterns derived from the historical data. The network then generated estimated wave height values based on the patterns learned during the training stage. These predicted values were subsequently compared and analyzed to identify the expected variation in wave height for the future observation period. The results of the sea wave height prediction using the Backpropagation algorithm are presented in the following table, which provides the predicted values for each month and year.

Table 2. Predicted Sea Wave Height for 2017–2020

No.	Month	2017	2018	2019	2020
1	January	2.51	2.31	2.27	2.28
2	February	2.91	2.72	2.68	2.68
3	March	2.42	2.34	2.33	2.33
4	April	2.48	2.67	2.72	2.72
5	May	2.48	2.36	2.32	2.31
6	June	2.52	2.55	2.59	2.63
7	July	2.22	2.20	2.26	2.28
8	August	2.55	2.68	2.70	2.70
9	September	2.54	2.42	2.37	2.34
10	October	3.02	2.84	2.77	2.75
11	November	2.26	2.33	2.34	2.33
12	December	2.57	2.63	2.66	2.67
	Highest	**3.02**	**2.84**	**2.77**	**2.75**
	Lowest	**2.22**	**2.20**	**2.26**	**2.28**
	Average	**2.54**	**2.50**	**2.50**	**2.50**

Source: Research Results.

The prediction outcomes indicate that sea wave height exhibited variations across the different months and prediction years. The maximum estimated wave height reached 3.02 m in October 2017, while the corresponding values for October were 2.84 m in 2018, 2.77 m in 2019, and 2.75 m in 2020. In contrast, the minimum predicted values occurred in July, with wave heights of 2.22 m, 2.20 m, 2.26 m, and 2.28 m for 2017, 2018, 2019, and 2020, respectively. The annual average predictions showed relatively limited variation, remaining between 2.50 m and 2.54 m throughout the 2017–2020 forecasting period. Overall, the results indicate that the Backpropagation model was able to produce monthly wave height estimates by utilizing patterns learned from the historical dataset during the training process. The resulting predictions can subsequently be incorporated as one of the environmental parameters in the analysis and modeling of coastal erosion conditions at Oesapa Beach.

2. Tidal Fluctuation Testing

The testing process for tidal fluctuations began with the preparation of the original tidal observations collected according to the corresponding observation period. The data were arranged chronologically by month and year to maintain the temporal sequence required for the subsequent modeling process. The original tidal fluctuation data used in this study are presented in Table 3. This table provides the initial observations before any normalization or transformation was applied, allowing the characteristics and variations of the tidal data to be identified directly from the original measurements. After the original data were compiled, the next stage involved preparing the observations for input into the Backpropagation model. Because the original tidal values have different numerical magnitudes, normalization was required to transform the observations into a consistent numerical range suitable for neural network processing. The normalized values obtained from this process were then used in the subsequent training, testing, and prediction stages of the Backpropagation model.

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Table 3. Monthly Average Tidal Fluctuations, 2010–2016

No.	Month	2010	2011	2012	2013	2014	2015	2016
1	January	1.4 m	1.4 m	1.5 m	1.3 m	1.4 m	1.5 m	1.0 m
2	February	1.4 m	1.4 m	1.4 m	1.3 m	1.4 m	1.5 m	1.0 m
3	March	1.4 m	1.4 m	1.4 m	1.5 m	1.4 m	1.5 m	1.2 m
4	April	1.5 m	1.4 m	1.4 m	1.5 m	1.5 m	1.5 m	1.3 m
5	May	1.5 m	1.5 m	1.3 m	1.4 m	1.5 m	1.5 m	1.8 m
6	June	1.4 m	1.5 m	1.3 m	1.4 m	1.5 m	1.6 m	1.2 m
7	July	1.4 m	1.5 m	1.4 m	1.6 m	1.4 m	1.5 m	1.8 m
8	August	1.6 m	1.5 m	1.4 m	1.6 m	1.4 m	1.5 m	1.4 m
9	September	1.5 m	1.5 m	1.6 m	1.5 m	1.4 m	1.5 m	1.5 m
10	October	1.6 m	1.4 m	1.4 m	1.5 m	1.5 m	1.5 m	1.5 m
11	November	1.4 m	1.4 m	1.4 m	1.4 m	1.3 m	1.4 m	1.2 m
12	December	1.4 m	1.4 m	1.4 m	1.4 m	1.3 m	1.3 m	1.7 m
	Highest	**1.6 m**	**1.5 m**	**1.6 m**	**1.6 m**	**1.5 m**	**1.6 m**	**1.8 m**
	Lowest	**1.4 m**	**1.4 m**	**1.3 m**	**1.3 m**	**1.3 m**	**1.3 m**	**1.0 m**
	Average	**1.4 m**	**1.4 m**	**1.4 m**	**1.4 m**	**1.4 m**	**1.4 m**	**1.3 m**

Source: BMKG East Nusa Tenggara.

Table 3 presents the monthly average tidal fluctuation data recorded at the study area during the 2010–2016 observation period. The data are organized according to month and year to illustrate the temporal variation in tidal conditions. Based on the table, the tidal values generally range from 1.0 m to 1.8 m. The highest annual value of 1.8 m was recorded in 2016, occurring in May and July, while the lowest value of 1.0 m was observed in January and February 2016. The annual average tidal fluctuation was relatively consistent, with values of approximately 1.4 m from 2010 to 2015 and 1.3 m in 2016. The distribution of the monthly observations indicates that tidal fluctuations vary between months and across years, although the overall range remains relatively narrow. In most years, the observed values fall between 1.3 m and 1.6 m, indicating relatively moderate temporal variation. The 2016 observations show a somewhat wider range, from 1.0 m to 1.8 m, compared with the preceding years. These variations provide important information for identifying the temporal characteristics of tidal conditions and serve as the initial dataset for the subsequent modeling process.

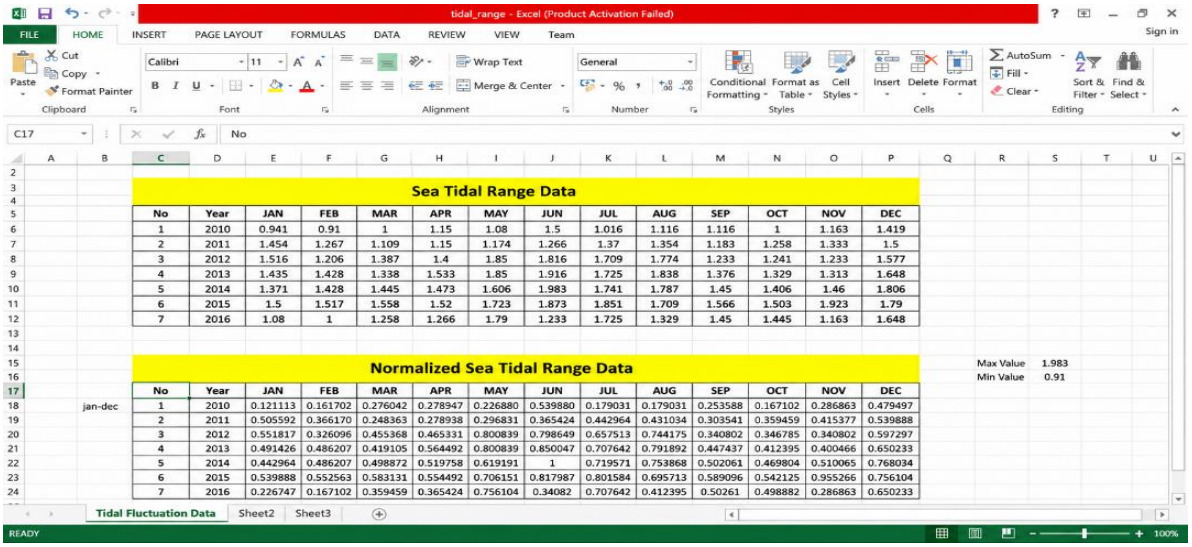


Figure 10. Results of sea level normalization using backpropagation

Figure 10 presents the results of the tidal fluctuation data normalization for the 2010–2016 observation period. The upper table contains the original monthly tidal range data, while the lower table shows the corresponding normalized values obtained after applying the normalization equation. Based on the dataset, the original tidal values have a maximum of 1.983 m and a minimum of 0.91 m, which are used as the reference values in the normalization

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process. The transformation produces values within a more consistent numerical range, with the normalized data subsequently serving as input for the Backpropagation training and testing processes. This step ensures that the tidal fluctuation data are appropriately scaled for neural network computation.

After the normalization and Backpropagation training and testing stages were completed, the trained network was used to generate future tidal fluctuation predictions. The prediction process utilizes the patterns learned from the historical tidal data to estimate the tidal conditions for each corresponding month in the prediction period. The resulting values provide an indication of the expected temporal variation in tidal fluctuations and can subsequently be incorporated as one of the environmental variables in the coastal erosion analysis. The results of the tidal fluctuation prediction using the Backpropagation algorithm are presented in the following table 4.

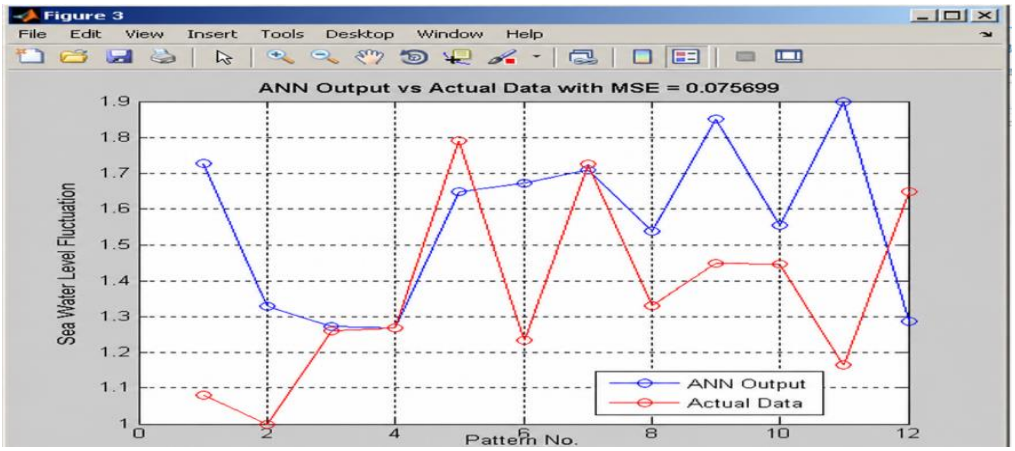


Figure 11. Output graph of sea tide testing using backpropagation

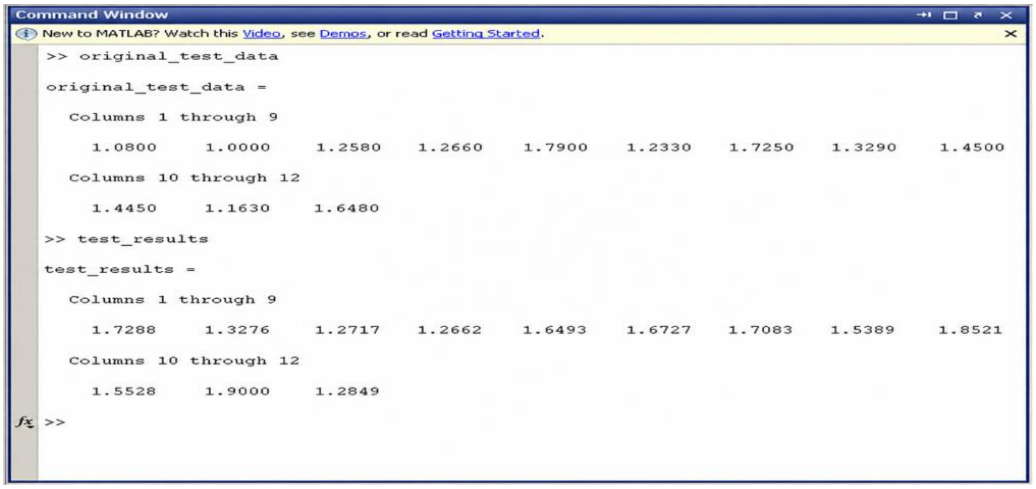


Figure 12. Comparison of actual data and testing data for sea level tides using backpropagation

Figure 11 presents the testing output of the sea tide fluctuation model generated using the Backpropagation algorithm, while Figure 12 shows the numerical comparison between the original testing data and the values produced by the trained network. The testing process uses 12 patterns, with the actual tidal values ranging from 1.0000 m to 1.7900 m. The corresponding Backpropagation outputs range from 1.2662 m to 1.9000 m. The graph indicates that the ANN output generally follows the variation of the actual tidal data, although noticeable differences occur at several patterns. The testing results produce an MSE of 0.075699, which represents the average squared difference between the model output and the actual observations. These results indicate that the trained network has learned the general pattern of tidal fluctuations and can subsequently be used for the next stage, namely tidal fluctuation prediction.

Following the completion of the testing stage, the trained Backpropagation model was applied to generate predictions of sea tidal fluctuations for the designated future period. The prediction was performed using the temporal patterns learned from the historical tidal dataset, with the resulting output representing the estimated tidal condition for each corresponding month. The predicted values were then organized chronologically to facilitate comparison and analysis of the expected changes in tidal fluctuations. The results of the sea tidal fluctuation prediction using the

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Backpropagation algorithm are presented in the following table, which summarizes the predicted values for each month and year of the prediction period.

Table 4. Predicted Tidal Fluctuations for 2017–2020

No.	Month	2017	2018	2019	2020
1	January	1.39	1.69	1.79	1.79
2	February	1.31	1.57	1.70	1.74
3	March	1.66	1.73	1.78	1.79
4	April	1.44	1.65	1.72	1.75
5	May	1.66	1.81	1.81	1.79
6	June	1.66	1.75	1.74	1.75
7	July	1.70	1.81	1.80	1.78
8	August	1.60	1.70	1.73	1.75
9	September	1.65	1.78	1.79	1.78
10	October	1.55	1.69	1.74	1.76
11	November	1.64	1.81	1.80	1.79
12	December	1.62	1.72	1.75	1.76
	Highest	**1.70**	**1.81**	**1.81**	**1.79**
	Lowest	**1.31**	**1.57**	**1.70**	**1.74**
	Average	**1.57**	**1.72**	**1.76**	**1.76**

Source: Research Results.

The forecasting outcomes reveal a general upward pattern in the estimated tidal fluctuations throughout the 2017–2020 period. The maximum predicted tidal level reached 1.81 m, which was recorded in both 2018 and 2019, whereas the minimum prediction was 1.31 m in February 2017. In terms of annual averages, the predicted value increased from 1.57 m in 2017 to 1.72 m in 2018, followed by a relatively consistent average of 1.76 m in 2019 and 2020. These findings suggest that the trained Backpropagation network was capable of capturing temporal patterns in the historical tidal dataset and using them to estimate monthly tidal conditions for the subsequent period. The resulting predictions can further be utilized as an input environmental parameter in the broader analysis of coastal erosion at Oesapa Beach, Kupang City.

3. Wind Speed Testing

The processing procedure for wind speed follows the same stages as those applied to sea wave height and tidal fluctuations. The process begins with the preparation of the original wind speed data, followed by normalization to transform the observations into a numerical range suitable for neural network processing. The normalized data are then used in the Backpropagation training and testing stages. After the testing process is completed, the trained network is applied to generate future wind speed predictions. This consistent procedure ensures that the three environmental variables are processed using comparable stages before being incorporated into the broader coastal erosion analysis.

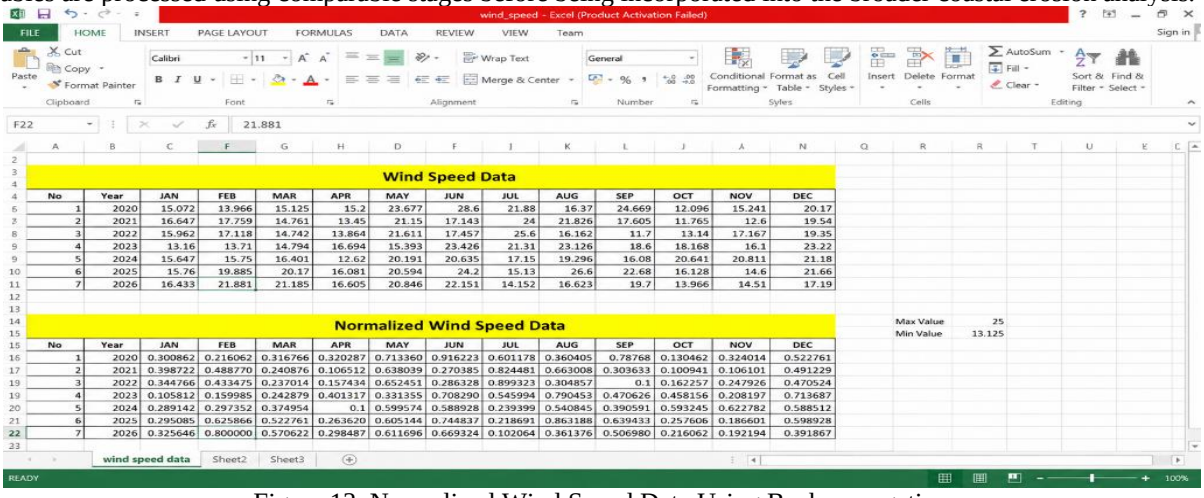


Figure 13. Normalized Wind Speed Data Using Backpropagation

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The results of the wind speed normalization process are presented in Figure 13. The figure shows the original wind speed observations together with the normalized values obtained after applying the normalization equation. The transformation converts the original measurements into a consistent numerical scale while maintaining the relative characteristics of the historical wind speed data. The normalized dataset obtained from this stage is subsequently used as input for the Backpropagation training process.

Following normalization and training, the performance of the trained network was evaluated using the wind speed testing data. The output generated by the Backpropagation network during the testing stage is illustrated in Figure 14, "Wind Speed Testing Output Graph Using Backpropagation." The graph presents the model output for each testing pattern and provides an overview of the network's ability to reproduce the variation in wind speed based on the patterns learned during training. The resulting output was then compared with the corresponding actual observations to determine the level of agreement between the predicted and observed values.

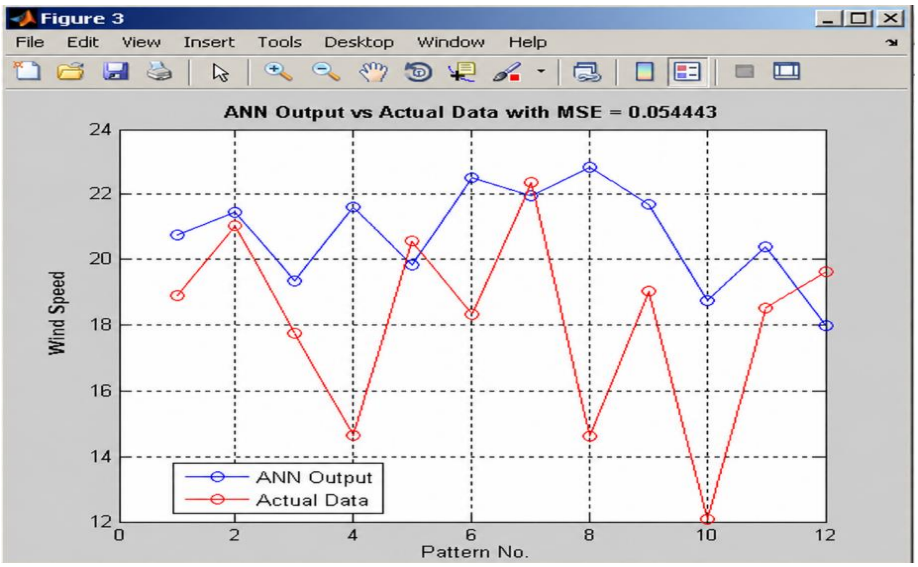


Figure 14. Testing Output Graph for Wind Speed Using Backpropagation

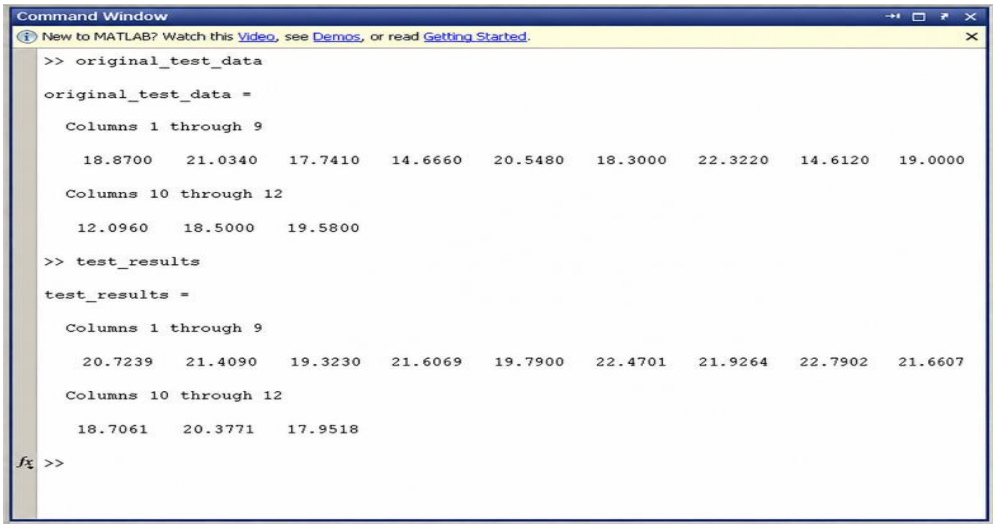


Figure 15. Comparison of Original and Tested Wind Speed Data Using Backpropagation

The comparison between the actual observations and the Backpropagation testing results is presented in Figure 15, "Comparison of Actual Data and Wind Speed Testing Data Using Backpropagation." The figure illustrates the differences between the actual wind speed values and the values generated by the trained network for each testing pattern. A smaller difference between the two series indicates that the model is able to represent the observed wind speed pattern more closely. The comparison is therefore used as an important basis for assessing the performance of the

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Backpropagation model before it is applied to the prediction stage. After the testing stage was completed, the trained Backpropagation network was subsequently used to generate wind speed predictions for the designated future period. The prediction process utilizes the patterns learned from the historical observations to estimate the wind speed for each corresponding month. The results of the Wind Speed Prediction Using Backpropagation are presented in Table 5. The table summarizes the predicted monthly wind speed values for each year in the prediction period, providing information on the expected temporal variation in wind conditions. These predicted values can then be used as one of the environmental variables, together with sea wave height and tidal fluctuations, in the subsequent coastal erosion prediction and analysis at Oesapa Beach, Kupang City.

Table 5. Predicted Wind Speed for 2017–2020

No.	Month	2017	2018	2019	2020
1	January	26.34	28.58	29.30	29.66
2	February	17.90	11.51	12.77	12.27
3	March	23.30	28.06	29.90	29.67
4	April	13.39	13.45	12.15	11.95
5	May	24.48	29.76	29.61	29.54
6	June	14.12	11.32	12.13	12.41
7	July	28.78	29.16	29.46	29.75
8	August	12.64	12.83	12.53	12.09
9	September	23.92	29.73	29.79	29.60
10	October	16.92	12.93	11.80	12.18
11	November	26.44	29.87	29.51	29.62
12	December	13.37	11.31	12.44	12.29
	Highest	**26.44**	**29.87**	**29.90**	**29.75**
	Lowest	**12.64**	**11.31**	**11.80**	**11.95**
	Average	**20.13**	**20.71**	**20.95**	**20.92**

Source: Research Results.

The forecasting outcomes reveal noticeable monthly fluctuations in wind speed throughout the prediction period. Relatively elevated wind speed values tend to appear in January, March, May, July, September, and November**,** whereas comparatively lower values occur in several of the other months. The maximum estimated wind speed reached 29.90 in March 2019, while the minimum was 11.31 in December 2018. In terms of yearly averages, the predicted wind speed increased from 20.13 in 2017 to 20.71 in 2018 and subsequently to 20.95 in 2019, followed by a minor reduction to 20.92 in 2020. These findings demonstrate that the Backpropagation network can produce monthly wind speed estimates by learning temporal patterns contained in the historical observations. The resulting wind speed predictions can be incorporated as an environmental parameter in the coastal erosion analysis at Oesapa Beach, Kupang City. Together with the predicted sea wave height and tidal fluctuations, the wind speed estimates provide the necessary environmental inputs for the subsequent coastal erosion prediction and modeling stage.

Figure 13 presents the normalized wind speed data used in the Backpropagation modeling process. The original wind speed observations for the 2010–2016 period were transformed into a standardized numerical range using the normalization procedure described previously, with the original dataset having a maximum value of 25 and a minimum value of 13.125. The resulting normalized values were subsequently used in the training and testing stages of the neural network. Figure 14 shows the testing output generated by the Backpropagation model for 12 testing patterns, with an MSE of 0.054443. The ANN output generally follows the variation of the actual wind speed data, although differences can be observed at several patterns. Meanwhile, Figure 15 presents the numerical comparison between the original testing data and the corresponding Backpropagation outputs. The original values range from 12.0960 to 22.3220, while the testing results range from 18.7061 to 22.7902, indicating that the model was able to identify the general pattern of wind speed variation, although some deviations remain between the estimated and observed values.

Based on the results of the normalization, training, and testing stages, the trained Backpropagation network was then applied to estimate future wind speed conditions. The resulting predictions for the 2017–2020 period are presented in Table 5. The prediction results show considerable monthly variation, with the highest estimated wind speed reaching 26.44 in 2017, 29.87 in 2018, 29.90 in 2019, and 29.75 in 2020, while the lowest values were 12.64, 11.31, 11.80, and 11.95, respectively. The annual average prediction increased from 20.13 in 2017 to 20.71 in 2018 and 20.95 in 2019, followed by a slight decrease to 20.92 in 2020. These results indicate that the Backpropagation model can generate monthly wind speed estimates from patterns learned from historical observations. The predicted wind speed values can

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subsequently be combined with the predicted sea wave height and tidal fluctuations as environmental input variables for the next stage, namely the coastal erosion prediction at Oesapa Beach, Kupang City.

Fuzzy Time Series-Based Testing

The testing and data processing stage using the Fuzzy Time Series (FTS) method was conducted to generate predictions based on the temporal patterns contained in the historical environmental data. The same three variables used in the Backpropagation approach, namely sea wave height, tidal fluctuations, and wind speed, were also considered in the FTS analysis. The data were first prepared according to the observation period and subsequently processed through the stages required by the Fuzzy Time Series method.

The Fuzzy Time Series procedure involves several stages, including the determination of the universe of discourse, partitioning the universe into appropriate intervals, defining fuzzy sets, performing the fuzzification process, establishing fuzzy logical relationships, and generating the corresponding forecasting results through the defuzzification stage. This procedure enables numerical environmental observations to be represented as fuzzy values while preserving their temporal characteristics. The resulting forecasts are then evaluated by comparing the predicted values with the actual observations.

1. **Sea Wave Height Testing Using Fuzzy Time Series**

The testing process for sea wave height using the Fuzzy Time Series (FTS) method was conducted to evaluate the capability of the model in identifying and forecasting patterns contained in the historical wave height data. The process began with the training stage, in which the historical data were processed to establish the temporal relationships required by the Fuzzy Time Series model. The training process produced an MSE of 2.7083×10^{-5} and an RMSE of 0.00520. These relatively small error values indicate that the model was able to follow the patterns in the training data with a low level of deviation. The results of the Fuzzy Time Series training and testing process are presented in Figure, as follows:

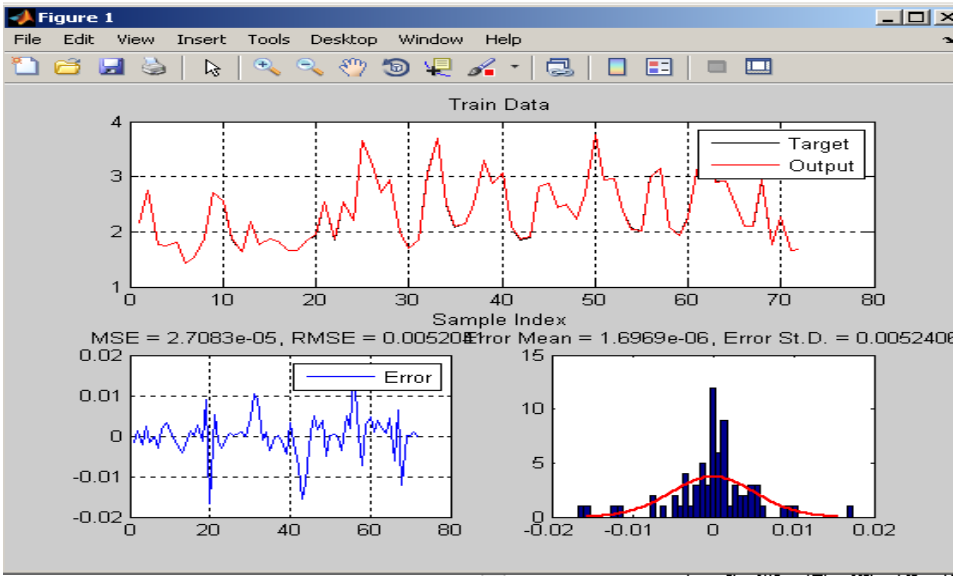


Figure 16. Wave Height Training Output Graph Using Fuzzy Time Series

Figure 17 presents the regression results obtained from the Fuzzy Time Series model for sea wave height. The regression plot is used to examine the relationship between the model outputs and the corresponding target values. The distribution of the plotted points and their proximity to the reference line indicate how closely the predicted values correspond to the target observations. This visualization complements the numerical evaluation of the model and helps identify differences between the predicted and observed wave height patterns. The regression results should be interpreted together with the testing error values to assess the predictive performance of the Fuzzy Time Series model.

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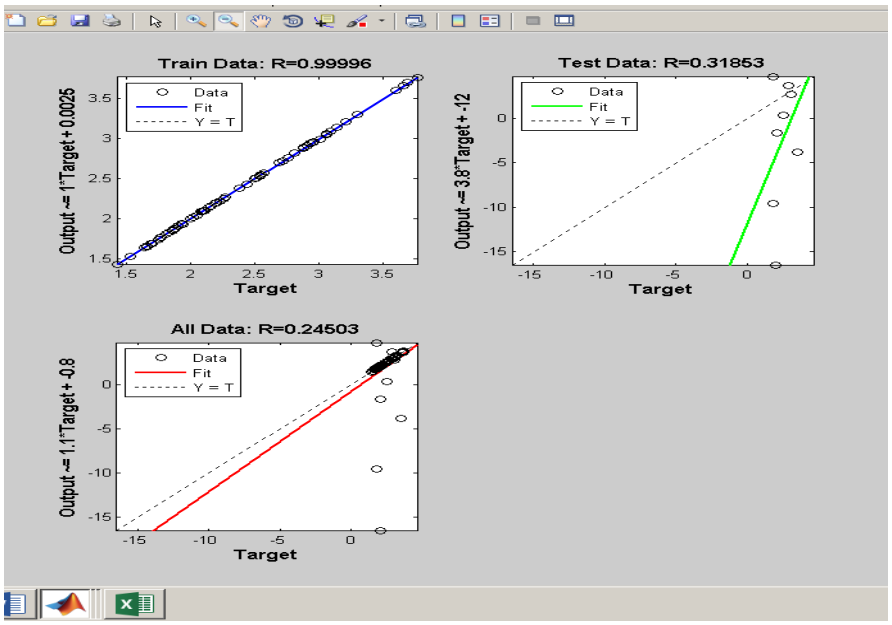


Figure 17. Fuzzy Time Series Wave Height Regression

Figure 18 presents the sea wave height prediction results generated by the Fuzzy Time Series model during the testing stage. The figure provides a visual basis for examining the correspondence between the predicted outputs and the target observations. Differences between the two series indicate prediction errors and reflect the model's ability to reproduce variations in sea wave height. These visual results should be considered alongside the quantitative testing metrics when assessing model performance. The evaluation is subsequently compared with the Backpropagation results to determine which method provides more accurate predictions for the environmental variables associated with coastal erosion at Oesapa Beach.

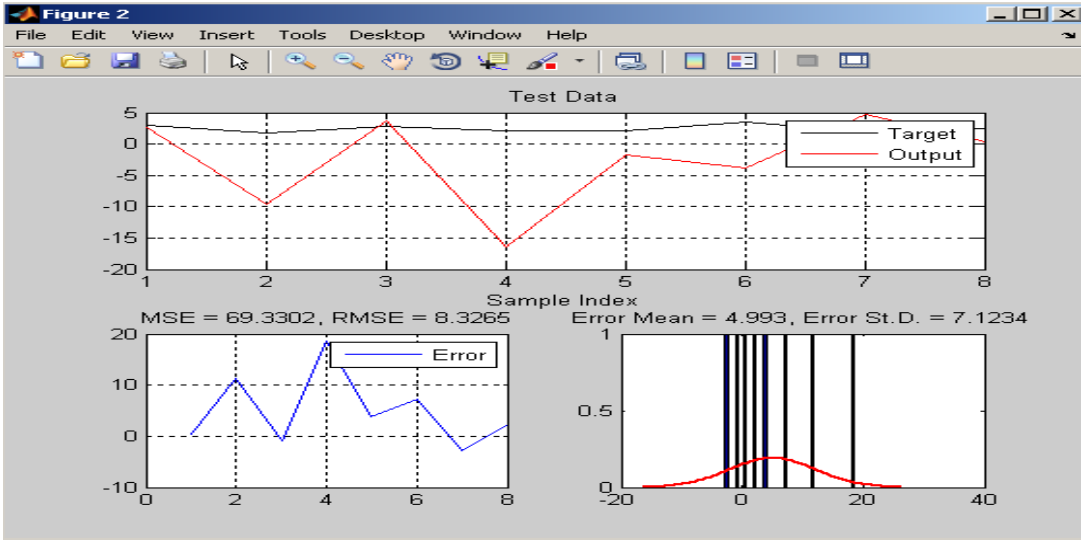


Figure 18. Fuzzy Time Series Testing Results for Sea Wave Height

The results shown in Figure 16 indicate that the performance of the Fuzzy Time Series model changed considerably when the model was applied to the testing data. The output generated by the model shows a substantial difference from the target values at several testing patterns. The testing process resulted in an MSE of 69.3302 and an RMSE of 8.3265. Compared with the training results, the considerably larger testing error indicates that the model was less capable of reproducing the target pattern in the testing dataset. This difference provides an important indication of the predictive capability of the Fuzzy Time Series model and becomes one of the considerations in evaluating its performance. Based on the Fuzzy Time Series calculation and forecasting process, the model was subsequently used to

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estimate sea wave height for the 2017–2020 period. The prediction results were arranged according to month and year to facilitate the identification of changes in the estimated wave height throughout the prediction period. The complete prediction results obtained from the Fuzzy Time Series method are presented in Table 6, as follows:

Table 6. Sea Wave Height Prediction for 2017–2020 Using Fuzzy Time Series

No.	Month	2017	2018	2019	2020
1	January	18.82	18.07	20.90	22.87
2	February	18.99	19.29	20.16	21.09
3	March	18.19	19.40	20.82	21.20
4	April	17.67	19.74	20.32	20.57
5	May	17.07	19.18	20.07	21.90
6	June	19.17	19.88	22.49	23.57
7	July	19.75	20.10	22.09	22.82
8	August	18.12	19.96	21.40	22.57
9	September	17.74	19.82	21.90	22.82
10	October	16.91	17.51	21.49	22.65
11	November	16.66	17.14	21.99	22.90
12	December	18.19	19.67	22.57	22.81
Highest	—	**19.75**	**20.10**	**22.57**	**23.57**
Lowest	—	**16.66**	**17.14**	**20.07**	**20.57**
Average	—	**18.11**	**19.15**	**21.35**	**22.32**

Source: Research Results.

The values presented in Table 6 show variations in the predicted wave height across the four-year prediction period. The highest predicted values were 19.75 in 2017, 20.10 in 2018, 22.57 in 2019, and 23.57 in 2020, while the lowest values were 16.66, 17.14, 20.07, and 20.57, respectively. The annual average predictions were 18.11 in 2017, 19.15 in 2018, 21.35 in 2019, and 22.32 in 2020. Overall, the prediction results indicate an increasing tendency in the estimated values from 2017 to 2020. These results are subsequently used as one of the environmental variables in the analysis of coastal erosion at Oesapa Beach, Kupang City. The results obtained from the Fuzzy Time Series method will then be compared with the predictions generated using the Backpropagation algorithm. This comparison is important because the primary objective of this research is not only to obtain future estimates of environmental conditions but also to determine which of the two approaches provides better predictive performance for modeling the environmental factors associated with coastal erosion at Oesapa Beach.

2. Tidal Fluctuation Testing Using Fuzzy Time Series

The Tidal Fluctuation Testing using the Fuzzy Time Series method was performed to evaluate the model's ability to identify temporal patterns in the historical tidal fluctuation data. The evaluation consisted of training and testing stages, in which the model output was compared with the corresponding target values. The training process produced a relatively low error, with an MSE of 1.9016×10^{-5} and an RMSE of 0.00438, indicating that the model was able to closely follow the patterns contained in the training dataset. The results of the tidal fluctuation training process using Fuzzy Time Series are presented in Figure 19, as follows:

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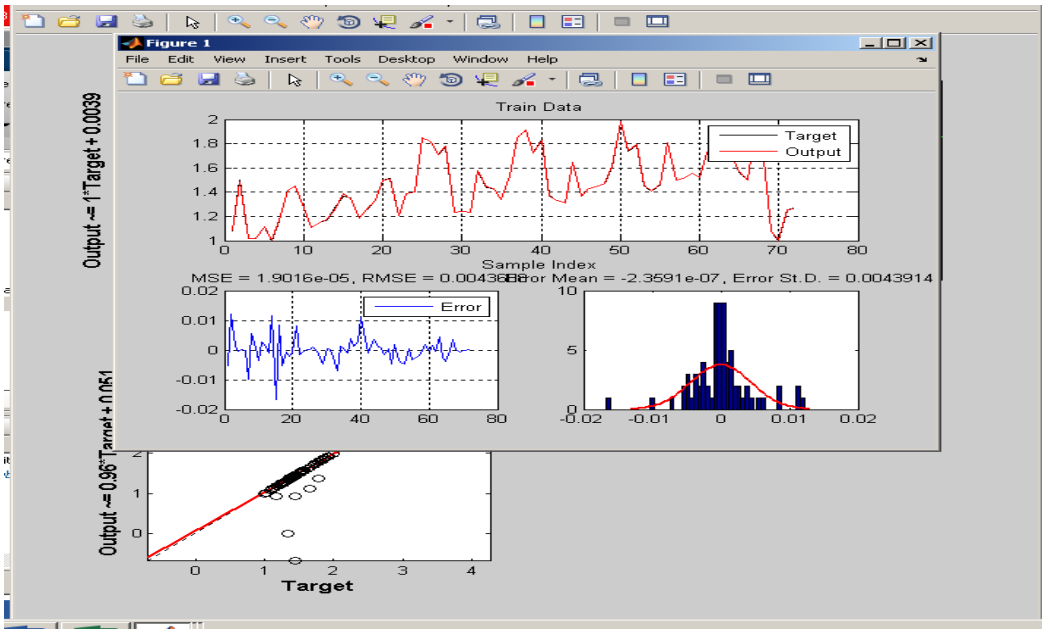


Figure 19. Tidal Fluctuation Training Graph Using Fuzzy Time Series

Figure 19 illustrates the relationship between the target values and the model output during the training stage. The output curve generally follows the pattern of the target data, which is reflected in the relatively small MSE and RMSE values obtained from the training process. The regression analysis was also performed to examine the relationship between the target data and the model output. The resulting regression performance for the training and testing datasets is presented in Figure 20, as follows:

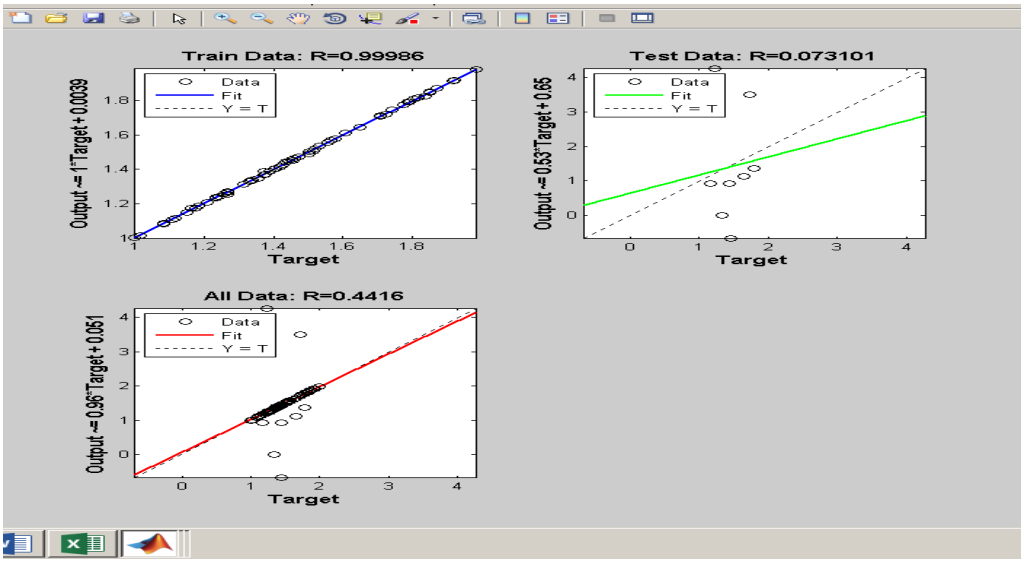


Figure 20. Tidal Fluctuation Regression Using Fuzzy Time Series

The regression results shown in Figure 20 provide an additional indication of the model's performance in representing the relationship between the target and output values. The training data demonstrate a considerably stronger relationship than the testing data, indicating that the model was able to learn the characteristics of the training observations effectively. However, the testing stage shows a weaker relationship, suggesting that the model performance decreases when applied to data that were not included during training. The detailed testing performance of the Fuzzy Time Series model is presented in Figure 21, as follows:

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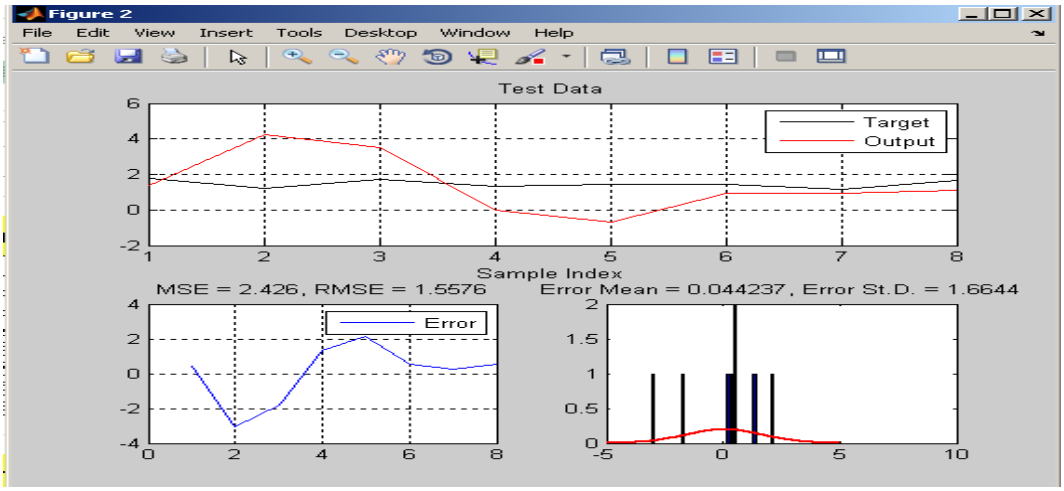


Figure 21. Tidal Fluctuation Testing Graph Using Fuzzy Time Series

Based on Figure 21, the testing process produces an MSE of 2.426 and an RMSE of 1.5576. These error values are considerably higher than those obtained during training, indicating that the Fuzzy Time Series model has a larger deviation when estimating the testing data. The difference between the training and testing performance indicates that the temporal patterns learned during training were not reproduced with the same level of accuracy in the testing dataset. Nevertheless, the trained Fuzzy Time Series model was subsequently used to generate future tidal fluctuation estimates. The resulting predictions for the 2017–2020 period are presented in Table 7, as follows:

Table 7. Tidal Fluctuation Prediction for 2017–2020 Using Fuzzy Time Series

No.	Month	2017	2018	2019	2020
1	January	8.37	9.12	10.34	9.01
2	February	7.18	10.81	9.12	10.22
3	March	8.03	7.46	9.32	8.34
4	April	6.49	9.00	8.17	8.25
5	May	8.23	9.39	8.39	8.64
6	June	9.03	9.25	9.22	7.25
7	July	10.12	8.39	8.37	9.32
8	August	9.88	8.12	10.20	9.07
9	September	9.00	9.32	7.55	7.97
10	October	7.76	9.10	7.22	7.27
11	November	9.39	10.50	7.37	9.14
12	December	9.03	9.17	9.25	6.27
Highest	—	**10.12**	**10.81**	**10.34**	**10.22**
Lowest	—	**6.49**	**7.46**	**7.22**	**6.27**
Average	—	**8.55**	**9.14**	**8.71**	**8.40**

Source: Research Results.

The prediction results presented in Table 7 show the estimated tidal fluctuation values for each month during the 2017–2020 prediction period. The highest predicted values were 10.12 in 2017, 10.81 in 2018, 10.34 in 2019, and 10.22 in 2020, while the lowest values were 6.49, 7.46, 7.22, and 6.27, respectively. The corresponding annual average values were 8.55 in 2017, 9.14 in 2018, 8.71 in 2019, and 8.40 in 2020. The results show variations in the predicted tidal conditions from month to month and between years. These prediction results are subsequently used as one of the environmental variables in the coastal erosion analysis at Oesapa Beach, Kupang City and will be compared with the corresponding predictions generated using the Backpropagation method.

3. Wind Speed Testing Using Fuzzy Time Series

The Wind Speed Testing using the Fuzzy Time Series method was conducted to assess the model's capability to recognize temporal patterns within the historical wind speed data. The evaluation involved training and testing stages, where the model-generated outputs were compared with the corresponding target values. The training process produced

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an MSE of 0.00084257 and an RMSE of 0.0290, indicating a relatively small error during the training stage. These results suggest that the model was able to reproduce the patterns contained in the training dataset with a high degree of consistency. The results of the wind speed training process using Fuzzy Time Series are presented in Figure 22, as follows:

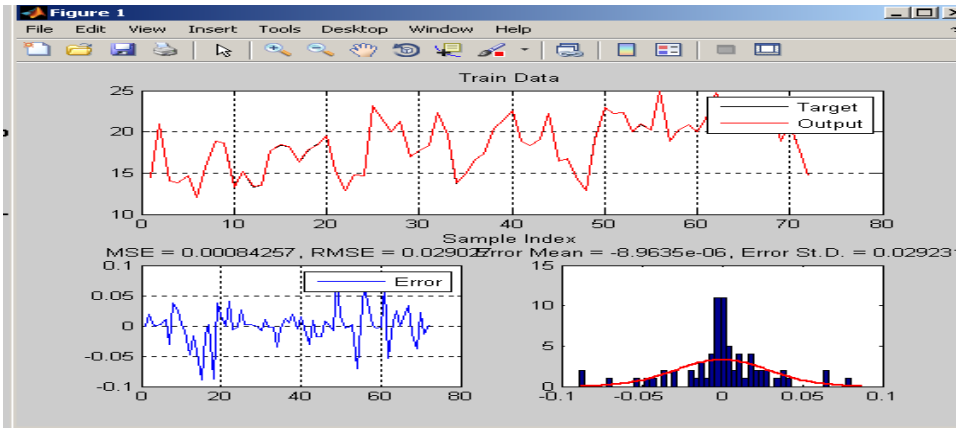


Figure 22. Wind Speed Training Graph Using Fuzzy Time Series

Figure 22 presents the comparison between the target values and the model output during the training process. The output curve generally follows the movement of the target data, which is consistent with the low MSE and RMSE values obtained during training. In addition to the training evaluation, regression analysis was performed to examine the relationship between the target observations and the model output. The regression results for the training and testing datasets are presented in Figure 23, as follows:

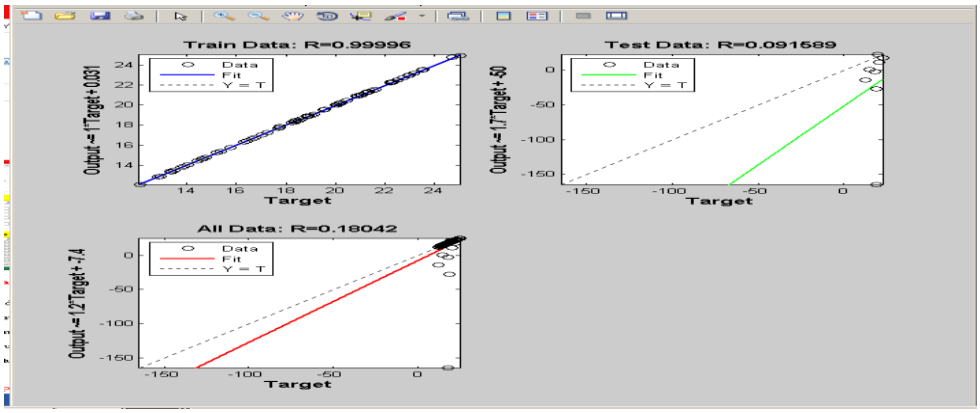


Figure 23. Wind Speed Regression Using Fuzzy Time Series

The regression results in Figure 23 indicate a very strong relationship between the target and output values in the training dataset, with a correlation coefficient of R = 0.99996. This result indicates that the Fuzzy Time Series model was able to represent the training data effectively. However, the testing dataset produced a considerably weaker correlation, with R = 0.091589. The substantial difference between the training and testing regression results indicates that the model's ability to generalize the learned temporal patterns was limited when applied to observations that were not included during the training process. The detailed testing performance of the Fuzzy Time Series model is presented in Figure 24, as follows:

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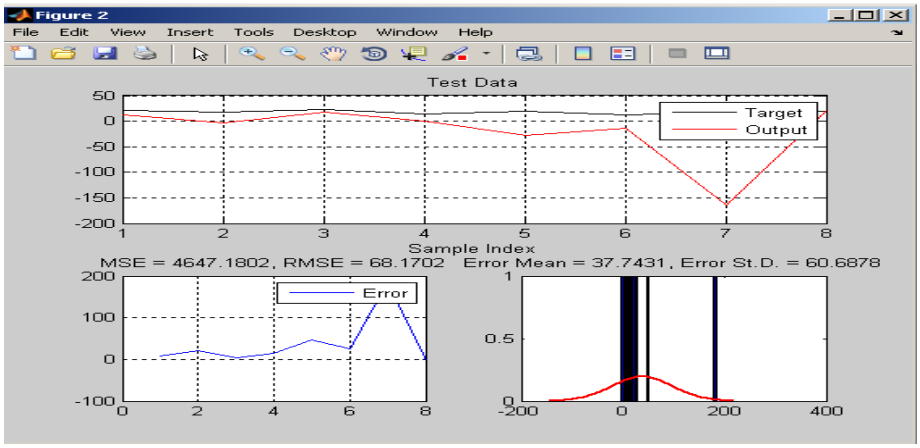


Figure 24. Wind Speed Testing Graph Using Fuzzy Time Series

Based on Figure 24, the testing process resulted in an MSE of 4647.1802 and an RMSE of 68.1702. These error values are substantially higher than those obtained during the training stage, indicating a considerable difference between the predicted outputs and the target values in the testing dataset. The results demonstrate that although the model achieved a very good fit during training, its performance decreased significantly when processing testing data. This condition suggests that the temporal patterns learned from the training data were not sufficiently generalized to the testing observations. Nevertheless, the trained Fuzzy Time Series model was subsequently applied to generate future wind speed estimates. The prediction results for the 2017–2020 period are presented in Table 8, as follows:

Table 8. Wind Speed Prediction for 2017–2020 Using Fuzzy Time Series

No.	Month	2017	2018	2019	2020
1	January	64.76	67.21	70.02	71.02
2	February	64.30	70.03	70.89	73.62
3	March	67.16	72.93	75.34	72.02
4	April	63.17	67.48	72.25	74.30
5	May	71.16	69.39	61.39	74.02
6	June	67.16	72.30	74.62	77.30
7	July	75.89	70.39	71.71	77.34
8	August	72.07	70.89	68.93	77.30
9	September	77.48	70.34	68.02	74.94
10	October	71.66	74.21	67.62	71.98
11	November	65.80	69.39	72.71	75.02
12	December	68.44	72.25	69.30	74.98
Highest	—	**77.48**	**74.21**	**75.34**	**77.34**
Lowest	—	**63.17**	**67.21**	**61.39**	**71.02**
Average	—	**69.08**	**70.57**	**70.24**	**74.49**

Source: Research Results.

The prediction results presented in Table 8 provide the estimated wind speed values for each month from 2017 to 2020. The highest predicted values were 77.48 in 2017, 74.21 in 2018, 75.34 in 2019, and 77.34 in 2020, while the lowest values were 63.17, 67.21, 61.39, and 71.02, respectively. The corresponding annual average values were 69.08 in 2017, 70.57 in 2018, 70.24 in 2019, and 74.49 in 2020. These results indicate that the predicted wind speed varies across months and years, with the overall annual average showing an increasing tendency toward 2020. However, given the relatively high MSE and RMSE obtained during the testing stage, the prediction results should be interpreted carefully. The resulting wind speed estimates are subsequently used as one of the environmental variables in the coastal erosion prediction process at Oesapa Beach, Kupang City and will be compared with the predictions generated using the Backpropagation method to determine which approach provides better predictive performance.

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Comparison of Backpropagation and Fuzzy Time Series Methods

Based on the training and testing results obtained from the Backpropagation and Fuzzy Time Series methods, a comparative analysis was conducted to assess the performance of both approaches in predicting coastal erosion at Oesapa Beach, Kupang City. The comparison focuses primarily on the prediction error represented by the Mean Square Error (MSE) for each environmental variable, namely sea wave height, tidal fluctuations, and wind speed. In addition, the comparison considers the resulting predicted erosion value to identify which method provides more consistent and reliable results for the coastal erosion prediction process. The comparison between the two methods is presented in Table 9, as follows:

Table 9. Comparison of Backpropagation and Fuzzy Time Series Results

No.	Comparison Aspect	Backpropagation	Fuzzy Time Series
1	MSE of Sea Wave Height	0.089607	69.3302
2	MSE of Tidal Fluctuations	0.075699	2.426
3	MSE of Wind Speed	0.054443	4647.1802
4	Predicted Coastal Erosion Value (2020)	0.52 m	2.02 m

Source: Research Results.

The results presented in Table 9 demonstrate a substantial difference in prediction performance between the two methods. The Backpropagation method consistently produces lower MSE values for all three environmental variables. For sea wave height, Backpropagation obtained an MSE of 0.089607, compared with 69.3302 for Fuzzy Time Series. Similarly, the MSE for tidal fluctuations was 0.075699 using Backpropagation, whereas Fuzzy Time Series produced 2.426. The largest difference was observed in wind speed, where Backpropagation achieved an MSE of 0.054443, while Fuzzy Time Series generated an MSE of 4647.1802. Since a lower MSE indicates a smaller difference between predicted and actual values, these results indicate that Backpropagation provides better predictive performance than Fuzzy Time Series for the three environmental variables considered in this study.

Furthermore, the predicted coastal erosion value for 2020 also shows a difference between the two approaches, with 0.52 m obtained using Backpropagation and 2.02 m generated by Fuzzy Time Series. The substantially lower prediction errors obtained from Backpropagation indicate that this method is more capable of learning the relationships among the environmental variables used in the study. Therefore, based on the comparative evaluation of MSE and the resulting erosion prediction, Backpropagation can be considered the more suitable method for predicting coastal erosion at Oesapa Beach, Kupang City, compared with the Fuzzy Time Series approach. The results also provide a basis for selecting Backpropagation as the primary method for interpreting the predicted coastal erosion conditions in the subsequent analysis.

DISCUSSION

The comparative results demonstrate that the Backpropagation algorithm achieved better predictive performance than Fuzzy Time Series (FTS) for the three environmental variables examined in this study. Backpropagation obtained MSE values of 0.089607 for sea wave height, 0.075699 for tidal fluctuations, and 0.054443 for wind speed, whereas FTS produced substantially higher MSE values of 69.3302, 2.426, and 4647.1802, respectively. These differences indicate that Backpropagation generated smaller prediction errors within the evaluation conducted. Its learning mechanism, which adjusts network weights iteratively to minimize the difference between predicted and target values, may help explain its performance in modeling the historical environmental data. In contrast, the higher errors obtained by FTS suggest that its forecasting results were less consistent with the target observations in this study. Nevertheless, these findings reflect the dataset and experimental procedures used and should not be generalized to all coastal environments or forecasting conditions.

The difference between the predicted coastal erosion values further illustrates the contrasting outputs of the two methods. Backpropagation estimated coastal erosion at 0.52 m in 2020, while FTS produced a prediction of 2.02 m. Together with the MSE comparison, these results support the selection of Backpropagation as the more suitable approach among the two methods evaluated for this study at Oesapa Beach, Kupang City. The findings demonstrate the potential of data-driven forecasting methods to support the analysis of environmental conditions associated with coastal erosion. However, the predicted erosion values should be interpreted cautiously because the reliability of the estimates depends on the quality of historical data, model configuration, and evaluation procedures. Further research using additional observations and independent validation would help assess the robustness of the predictions and strengthen their potential application in coastal management and erosion mitigation planning.

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CONCLUSION

Based on the results of the study, the Backpropagation and Fuzzy Time Series methods were applied to predict coastal erosion at Oesapa Beach, Kupang City, using three environmental variables: sea wave height, tidal fluctuations, and wind speed. The analysis shows that Backpropagation produced lower prediction errors for all three variables, with MSE values of 0.089607 for wave height, 0.075699 for tidal fluctuations, and 0.054443 for wind speed. In comparison, Fuzzy Time Series produced MSE values of 69.3302**,** 2.426, and 4647.1802, respectively.

The comparison results indicate that Backpropagation provides better and more consistent predictive performance than Fuzzy Time Series in this study. The predicted coastal erosion value for 2020 was 0.52 m using Backpropagation, while Fuzzy Time Series produced 2.02 m. Therefore, Backpropagation was identified as the more suitable method for modeling and predicting coastal erosion conditions at Oesapa Beach, Kupang City, based on the environmental variables analyzed.

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