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LOW EMISSION DEVELOPMENT STRATEGIES AND SUSTAINABLE DEVELOPMENT GOALS

Sea-level projections using a NARX-NN model of tide gauge data for the coastal city of Kuala Terengganu in Malaysia

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Abstract

The impact of global warming presents an increased risk to the world's shorelines. The Intergovernmental Panel on Climate Change (IPCC) reported that the twenty-first century experienced a severe global mean sea-level rise due to human-induced climate change. Therefore, coastal planners require reasonably accurate estimates of the rate of sea-level rise and the potential impacts, including extreme sea-level changes, floods, and shoreline erosion. Also, land loss as a result of disturbance of shoreline is of interest as it damages properties and infrastructure. Using a nonlinear autoregressive network with an exogenous input (NARX) model, this study attempted to simulate (1991 to 2012) and predict (2013–2020) sea-level change along Merang kechil to Kuala Marang in Terengganu state shoreline areas. The simulation results show a rising trend with a maximum rate of 28.73 mm/year and an average of about 8.81 mm/year. In comparison, the prediction results show a rising sea level with a maximum rate of 79.26 mm/year and an average of about 25.34 mm/year. The database generated from this study can be used to inform shoreline defense strategies adapting to sea-level rise, flood, and erosion. Scientists can forecast sea-level increases beyond 2020 using simulated sea-level data up to 2020 and apply it for future research. The data also helps decision-makers choose measures for vulnerable shoreline settlements to adapt to sea-level rise. Notably, the data will provide essential information for policy development and implementation to facilitate operational decision-making processes for coastal cities.

Keywords NARX · Time series · Environmental data analysis · Climatic · Shoreline · Simulation

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Introduction

While the number of people living in coastal areas is growing, nearly 70% of the world's coastal is receding. Only 20% of the land is considered stable, while the remaining 10% is assessed to be in an advanced state of retreat (Bagheri et al. 2021a). According to the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC), global sea levels will increase by 18–59 cm by 2100. (Sudipta et al. 2021).

It is evidenced by the recently reported accelerated decline of polar ice sheet masses (2–5) and makes future sea-level rises of 1 m or more by 2100 a real possibility (Pfeffer et al. 2008). With rising sea levels, a significant loss in assets is expected. The predicted sea level from global climate change is likely to impact shoreline systems throughout the world significantly. Significant numbers of coastal assets worldwide are susceptible to damage from flooding and erosion. It happens when climate change events at sea drive storm surge toward the shorelines, leading to a localized rise above normal tide levels that can result in flooding and erosion of the immediate and surrounding shoreline areas. Therefore, a critical scientific endeavor is a better understanding of shoreline response to changes in sea level to inform policy and decision making. The examination of tidal gauge observation data during the twentieth century revealed that the global sea level would rise by an average of 1.70.5 mm/year (Bindoff et al. 2007).

Ibrahim and Wibowo (2013) reported that flooding incidences have constantly been throughout Kuala Terengganu. The Dungan district, for example, experiences floods almost on an annual basis, mainly when the river water level rises a few meters above a harmful level. Floods were often caused by direct runoff from rivers or tidal surges from the ocean.

Gasim et al. (2007) reported that over 70% of Terengganu is classified as a low-lying coastal area of fewer than 200 m in altitude, and approximately 30% of the area is considered vulnerable to flash floods. The northeast monsoon contributed to flooding events in Southern Thailand and the eastern region of Malaysia, including the Kelantan Province, situated in the Northeastern part of Peninsular Malaysia. There, floods affect nine out of ten townships. One of the characteristics of the monsoon season is the heavy annual rainfall lasting from October to March that causes severe floods in most of Terengganu, especially around November and December. In December 2004, Terengganu and several other states in Malaysia, such as Perak, Perlis, Kelantan, and Pahang, were exposed to heavy rainfall that caused one of the most severe flooding events. During this time, the National Security Council (Majlis Keselamatan Negara, MKN) moved more than 100 000 people from the affected areas to relief centers (MERCY 2014). Over time, widespread coastal inundation can modify water quality and the characteristics of groundwater, leading to the loss of properties and life, adversely impacting agricultural production, harming the tourism industry, and discouraging recreation (Doong et al. 2009).

There are several causes for sea-level change (Bird 2011; Church et al. 2010): firstly, the sea level's steric effects and eustatic movement typically decrease or increase the water volume in the ocean basins. Secondly, water mass exchange with continents leads to variability in sea level. Thirdly, elastography affects the dispersal of meltwater of ice sheets which often causes uneven spatial variations in sea level. In essence, sedimentation and tectonic movements lead to variations in sea level. In addition, the downward or upward movements of the Earth's crust can cause sea levels to increase or decrease. Due to climate change, sea-level rise is occasionally called anthropogenic (Hassan 2002; Bird 2011; Mitrovica et al. 2001; Church et al. 2010; Tjia 1992 1996).

Sea-level variation can alter marine habitats, natural coastal processes, and ecosystems. Experience has proven that sea-level change can affect coastal infrastructure and adversely impact Malaysia's socio-economy. Nevertheless, these impacts can be minimized and alleviated with knowledge and adequate preparedness. Otherwise, coastal cities will suffer from susceptibility, vulnerability, hazard, and risk from sea-level rise impacts. It highlights the importance of science-based coastal city assessments, including tide gauge data analysis, to better predict sea-level change.

Here, we focus on Kuala Terengganu to exemplify how such a study can assist coastal and shoreline decision-makers in developing policies and strategic action plans. This research reviewed sea-level statistical analysis from tide gauge data (1991–2012).

This research aims to critically analyze, examine trends, and assess the stochastic aspects of existing and forecasted sea-level data from tide gauge stations on Peninsular Malaysia's East Coast.

The following are the two specific goals of this project: to see how much local climatic knowledge can increase the precision of the simulation and projections of sea level. Secondly, on the Kuala Terengganu shoreline area, compare the simulation and forecast effects of tidal gauge stations using the NARX model.

Climate change and sea-level rise

Monitoring shoreline changes offer essential insights for predictions on the potential impacts on coastal economic development and land management (Welch et al. 1992). Over the past 15–20 years, scientific assessments of climate change

that consider human dimensions have improved considerably (Moser 2005; Rayner and Malone 1998). The sea level is potentially rising (Nicholls and Cazenave 2010). The impact of the Greenland and West Antarctic ice sheets on regional sea-level variations is one of the most significant. Regardless, sea levels have been rising since the twentieth century (Boateng 2012) and continue to rise at an accelerated rate.

N.A.H.R.I.M. has done several studies on imminent global warming issues, including sea-level rise forecasts in Malaysia, shoreline vulnerability assessments for high-risk locations, and the creation of potential sea-level rise inundation maps (Awang and Abd Hamid, 2013). The east coast of Peninsular Malaysia is vulnerable to sea-level rise. According to previous research, the northeast monsoon in 1997 caused a 50 cm rise in sea level and a 1 °C decrease in coastal water temperature in Kuala Terengganu (Taira et al. 1996). In 60 years, Malaysia's temperature and rainfall are projected to climb by + 0.6 to 3.4 °C and − 1 to 32%, respectively, while the sea level is expected to rise by around 13–94 cm (Bagheri et al. 2019). As a result, these could influence water resources, the coastal zone, flood control, public health, and other areas, requiring national and international actions to combat climate change (Begum et al. 2011). However, a holistic assessment of the effect of sea-level rise on the shoreline zone is required to design appropriate adaptation measures that would limit the possible consequences of sea-level rise on the shoreline zone. Flooding, erosion, and shoreline change are significant issues along Peninsular Malaysia's eastern coast, particularly in the South China Sea (Boateng 2012).

Many researchers assume a proportional relationship between climate factors and sea level. Therefore, the rate of the sea-level rise should increase in concert with increases in climate factors. Rainfall is one factor that needs to be monitored. Peninsular Malaysia's rainfall averages approximately 2,540 mm annually, though rainfall distribution patterns vary and depend on local topography and seasonal wind flow (Raj 2000). Rainfall patterns along the East Coast indicate wider seasonal variation, with a maximum recorded in November, December, and January, whereas the driest months in most districts, are between June and July (Nieuwolt 1965; M.M.S. 1999). In 2012, the Dungun district was severely hit by a monsoon flood, with floodwaters reaching up to 1.5 m in height (Ishak et al. 2014). The geographical location of Kuala Terengganu near the equator makes it vulnerable to two distinct monsoon seasons, namely the Southwest monsoon (May to September) and the Northeast monsoon (October to March).

Another issue to keep an eye on is the wind, which affects the behavior of waves despite being light and unpredictable in Malaysia. Several flow patterns exist relating to the Northeast monsoon, the Southwest monsoon, and two shorter interim monsoon seasons. During the Southwest monsoon (end of May/early June to September), the predominant wind flow comes from a south-westerly direction at light wind speeds (< 15 knots). In contrast, steady easterly or north-easterly winds at l0–20 knots dominate the northeast monsoon from early November to March. The two shorter inter-monsoon seasons have winds that are usually light and variable. The monsoon winds that occur during the Northeast monsoon, the primary rainy season in Malaysia, influence the magnitude and direction of waves. Strong waves are widespread during this time.

Tide gauge stations of Peninsular Malaysia

There are 21 tidal stations located along with Peninsular Malaysia. The height of the nearest benchmark (B.M.) refers to four entities:

1. Elevation above the Land Survey Datum (L.S.D.) was determined at Port Klang in 1912 by the British Admiralty for all northern stations in Peninsular Malaysia.
2. Elevation above the Peninsular Malaysia Geodetic Vertical Datum (P.M.G.V.D.) was determined from tidal observations at Port Klang from 1984 to 1993 for all southern stations in Peninsular Malaysia.
3. Elevation above the Kota Kinabalu datum 1975 (East Pillar), for the station in Kota Kinabalu.
4. Elevation above the Belfry Datum 1918, for the station located in Tawau.

All 21 tidal stations are of the float type and manufactured by Kyowa Shoko Co. Ltd., Japan. They all use the IC-Memory cassette digital recording system (Table 1). These tide gauges have a set mode whereby every sampling interval can be set as needed. The tidal values are averaged by the built-in microprocessor and recorded on the IC-Memory cassette. The sampling interval set by Jabatan Dan Pemetaan Malaysia (J.U.P.E.M.) is every 10 s and input data are averaged every 50 s.

Artificial neural network model

In theory, artificial neural networks (ANNs) present significant advantages compared to standard statistical methods. Neural networks automatically permit indiscriminate nonlinear relationships between the dependent and independent variables and all potential interactions between the dependent variables. Hence, the standard statistical methods necessitate supplementary modeling to tolerate this flexibility. Moreover, ANNs do not require obvious distributional assumptions (Sargent 2001). ANNs that can estimate nonlinear mathematical functions (Hornik 1993) make it possible

Table 1 Description of the Peninsular Malaysia tidal stations

No	Station	Location	Latitude (N)	Longitude (E)	Established value (m)	Height of nearest BM (m)	Date established	Zero of tide gauge at tidal station	Situated
1	Pulau Langkawi	Jeti Telok Ewa	06 25.9	99 45.9	6.633	3.417(K 0172)	Nov. 1985	5.545 m below survey department brass BM K0172 or 2.128 m below L.S.D. 1912	Near the tidal station at the Kedah Cement Jetty, Telok Ewa
2	Pulau Pinang	Penang Yacht Club George Town	05 25.3	100 20.8	6.732	2.427(p 0379)	Nov. 1984	4.962 m below survey department brass BM P0379 or 2.535 m below L.S.D. 1912	At Cornet of Fort Cornwallis
3	Lumut	Pengkalan T.L.D.M	04 14.4	100 36.8	7.029	3.517 (A 0401)	Nov. 1984	5.685 m below survey department brass BM A0401 or 2.168 m below DTGSM	In front of the tide station at Jetty B1, Royal Malaysian Naval Base
4	Pelabuhan Kelang	Dermaga 25 pelabuhan utara	03 03.0	101 21.5	8.640	3.870 (B 0169)	Dec. 1983	7.494 m below survey department brass BM B0169 or 3.624 m below DTGSM	Behind the tidal station at Wharf No.25 North Port
5	Tanjung Keling	Jeti Tanjung Bruas	02 12.9	102 09.2	7.429	3.668 (M 0331)	Nov. 1984	6.427 m below survey department brass BM M0331 or 2.759 m below DTGSM	At Jetty
6	Kukup	Jeti	01 195	103 26.6	8.432	3.011 (J 1323)	Nov. 1985	6.884 m below survey department brass BM J1323 or 3.873 m below DTGSM	At Jetty
7	Johor Bahru	Jeti Kastam Johor Bahru	01 27.7	103 47.5	7.034	3.422 (J 0416)	Dec. 1983	6.079 m below survey department brass BM J0416 or 2.657 m below DTGSM	Beside the steps at the beginning of the Custom Jetty
8	Tanjung Sedili	Kompleks LKIM	01 55.9	104 06.9	5.930	2.257 (J 0801)	Oct. 1986	4.459 m below survey department brass BM J0801 or 2.202 m below DTGSM	At the Fisheries Complex Jetty
9	Pulau Tioman	Jeti Berjaya Kuantan	02 48.4	104 08.4	7.930	Tidak diperolehi (C 0501)	Nov. 1985	6.586 m below survey department brass BM C0501	At the jetty in front of the tidal station
10	Tanjung Gelang	Pelabuhan Kuantan	03 58.5	103 11.2	7.731	3.835 (T 0283)	Dec. 1983	6.496 m below survey department brass BM C0331 or 2.661 m below DTGSM	At the left corner of the bridge at Petronas Depot, Kuantan Port

Table 1 (continued)

No	Station	Location	Latitude (N)	Longitude (E)	Established value (m)	Height of nearest BM (m)	Date established	Zero of tide gauge at tidal station	Situated
11	Chendering	Kompleks LKIM	05 15.9	103 11.2	6.732	2.604 (T 0283)	Oct. 1984	4.688 m below survey department brass BM T0283 or 2.084 m below DTGSM	At the left corner of T-junction facing Tidal Station
12	Geting	Kompleks LKIM	06 13.6	102 06.4	7.230	3.852 (D 0354)	Oct. 1986	5.964 m below survey department brass BM D0354or 2.112 m below DTGSM	At the entrance of the walkway to the tidal station
13	Sejingkat	Pelabuhan	01 34.9	110 25.3	10.533	3.405 (BM 10,001)	Feb. 1996	8.983 below survey department brass BM No.10001	At Jetty
14	Bintulu	Pelabuhan	03 15.7	133 03.8	7.343	3.745 (BM 1641)	Jul. 1991	5.795 m below survey department brass BM 1641	At Jetty
15	Miri	Marina Park. Miri	04 24.1	113 58.5	7.812	4.858 (No. QM 0002)	Jun. 1991	6.866 m below survey department brass B.M. No. QM0002	Beside the light house
16	Kota Kinabalu	Pelabuhan	05 59.0	116 04.0	7.230	3.783 (No. 2018)	Jun. 1987	6.179 m below survey department brass B.M. 2018 or 2.396 m below Kota Kinabalu Datum (East Pillar)	At jetty in front of tidal station
17	Kudat	Pelabuhan	06 52.8	116 50.6	7.000	2.784 (BM 205,004)	Oct.1995	5.414 m below survey department brass BM 205,004	At jetty in front of tidal station
18	Sandakan	Pelabuhan	05 48.6	118 04.0	7.500	3.270 (No.SS1)	Aug. 1993	5.976 m below survey department brass BM SS1	At jetty in front of tidal station
19	Lahad Datu	Pelabuhan	05 01.1	118 20.8	7.500	2.934 (LDU 1)	Oct. 1995	5.734 m below survey department brass BM LDU1	At jetty in front of tidal station
20	Tawau	Pelabuhan	04 14.0	117 53.0	7.425	3.540 (No. 5113)	Jun. 1987	6.116 m below survey department brass BM 5113 or 2.576 m below Belfry Datum	At jetty in front of tidal station
21	Labuan	Pelabuhan	05 16.4	115 15.0	7.300	2.924 (LBU 0001)	Des. 1995	5.848 below survey department brass BM LBU0001	At jetty in front of tidal station

Source: J.U.P.E.M. 1997.

to simulate a complicated behavior system without knowing the fundamental relationships between its elements (Haykin 1999). The information processing system structure of these models is unique. The advantages of ANNs over other methods stem from their ability to self-learn, allowing them to describe the fundamental relationships between input and output variables without requiring prior knowledge of the nature of the association. Zhao et al. (2012) noted that this advantage makes ANNs suitable for complex nonlinear problems that cannot be analytically resolved. This advantage renders ANN models superior to other traditional statistical models, such as the Multiple Linear Regression (MLR) models, which are inappropriate for non-normally distributed data (Masters 1993). Another adaptability of ANN is its capacity to resolve specific problems.

ANN models are organized in many interconnected processing neurons or nodes that work in unity. They work as a black-box model without requiring comprehensive system information because ANN uses historical data to study the connection between input and output parameters. They constitute powerful tools for modeling (Lek et al. 1996; Lek and Guégan 1999; Mas et al. 2004). ANNs can learn from their surroundings through the representation of diverse samples and via learning algorithms. Every time an ANN model is generalized, it can connect any input data correctly, irrespective of whether they were utilized during the learning stages. ANNs could be described as estimators of semi-parametric regressions. Hence, they can access virtually any (measurable) function to an indiscriminate amount of accuracy (Hornik et al. 1989). They appeal to many researchers due to their similarity to the human brain. They appear to provide "prediction" without the problems connected with the utilization of mathematics. Eftekhar et al. (2005) noted that the challenge in developing ANN models is the absence of set methods to construct the network architecture.

Data requirements

We obtained re-analyzed and primary data from various websites and departments for this study. It comprised monthly observed tide gauge data from Kuala Terengganu and data on sea surface temperature (SST), rainfall, wind, and Sea-Level Pressure (SLP). The observed monthly tide data were obtained from the Department of Survey and Mapping Malaysia (J.U.P.E.M., Geodetic Survey Division, Vertical Reference Section Infrastructure). The Malaysian Meteorological Department (MMD) provided monthly rainfall and wind speed data. The National Centre for Environmental Prediction (N.C.E.P.) also provided re-analyzed data for SST and SLP.

The analysis system software in J.U.P.E.M. was utilized to predict monthly tide gauge data to forecast changes in sea levels. Monthly anticipated wind data were obtained from the MMD. In contrast, data on the monthly anticipated rainfall was sourced from the Research Centre for Tropical Climate Change System (I.K.L.I.M.) of the National University of Malaysia (U.K.M.). The projection of rainfall was analyzed using the Had CM3-PRECIS climate model. The study discusses the results of the configuration and validation of the PRECIS regional climate simulation (Kwan et al. 2014), while the NCEP-PCM1 provided the data on SST and SLP.

The study has several database limitations: First, there is insufficient data. There are inadequate tide gauge stations along Malaysia's coast. On average, each state has only one tide station. Studies of this nature require at least two or three stations. Secondly, insufficient time-series data. The third constraint was the high cost of the program. The fourth constraint, as mentioned previously, concerned the reporting and research gathered from Malaysian government agencies.

Time series analysis

Time-series data are chronologically ordered data (Amerian and Vosooghi, 2011). Mean sea-level (MSL) daily observation data enables the analysis of historical records at tide stations which offers evidence of nonlinear change in sea level. This present study analyses a time series of Observed Tide Gauge (OTG) documented at Chendering station (situated in Terengganu state, Long: 103° 11′ 12″ E and Lat: 5° 15′ 54″ N) between 1991 and 2012. Based on that, the Sea-Level Residual (SLR) for sea-level rise prediction was generated. Before that, the study conducted statistical investigations of the OTG to detect any outliers and missing data.

The OTG data were utilized to simulate Tide Gauge (SDG) with the aid of the tide analysis software system at J.U.P.E.M. in 2012. The first Tide Gauge Processing System (TGPS) Model software was applied by Jabatan Ukur dan Pemetaan Malaysia and coined accordingly as J.U.P.E.M. It was built for the MS-DOS environment, and most modules were in command prompt form (J.U.P.E.M., 2014). Top Optics Sdn Bhd managed the second version development of the TGPS software on behalf of J.U.P.E.M. Top Optics Sdn Bhd drove this initiative to upgrade the original system to a new operating system (Windows 98 using Visual Basic 5.0). The software will require further development and enhancement to adapt to current operating system standards and enhance efficiency in data processing, printing tide graphs, etc. Tide's new TGPS software will be developed using the visual primary 6.0 language with the help of Microsoft Access as a data keeper for the Microsoft Windows XP operating system.

Before a simulation (2019 to 2012) and prediction (2013 to 2020) of sea level using the NARX model for the Kuala Terengganu area, the Sea-Level Residual (SLR) for the tide gauge station from 1991 to the 2012 year should

be estimated and can be calculated with the Tide Gauge Observed (TGO) and Tide Gauge Simulated (TGS) data (1991 to 2012) (TGO – TGS = SLR). SLR is time-series data utilized as an output simulator in the NARX model for simulation learning (Bagheri et al. 2021a, 2019).

Since October 1984, the Zero of the Tide Gauge (Z0) for the Chendering tide station has been constant (J.U.P.E.M. 1997). The OTG was obtained from the Department of Survey and Mapping Malaysia (J.U.P.E.M.) (Fig. 1). The mean of the Datum level is approximately 105.4 (cm), and a Minimum of 96.7 (cm) and a maximum of 114.5 (cm) were noted.

Sea-level rise would be an increasing problem in the study area, leading to more significant shoreline erosion in the region because the study area is primarily low-lying coastal plains. It could endanger the residents who live in these places and the coastal environment. This study's findings could aid in developing a new sea-level rise trend, and the findings could be used as part of a coastal vulnerability assessment. The findings could also suggest prioritizing conservation measures in degraded regions and initiating decisions to manage sea-level rise impacts adaptively. One of the most challenging aspects of maintaining coastal environments is determining which areas are at risk.

Artificial neural networks model

A vital component of artificial neural networks (ANN) is how it processes mathematical information, much akin to how a cerebral nervous system would (Birdi et al. 2013; Kruse et al. 2011). It consists of several vastly corresponding computational nodes or processing neurons which work together to solve particular problems under a connectionist approach to computation. By obtaining a weighted input, the related output is generated by the node with the use of an activation function. Numerous neurons can be amalgamated into one layer.

Essentially, an ANN can comprise one or more interrelated layers of neurons in which all the neurons are linked. While the new information is admitted through the input layer, the hidden layers process this information, and the outcome of the network is presented in the output layer. According to Bishop (1995), the configuration of interrelationships between the nodes in the layers is known as architecture. Generally, the architecture of ANN comprises an input layer, an output layer, and one or more hidden layers. The main feature entails processing information characteristics in high-parallelism, nonlinear, fault, and noisy environments with generalization and learning abilities (Polo et al. 2015).

Li et al. (2020) say that neural networks can make generalized models by being trained on available datasets. Conversely, a trained net can categorize data from the identical category as the trained dataset that has not been previously seen. The input data were normalized to increase training efficiency (Taoufik et al. 2022). Before using the neural network model, it is necessary to pre-treat the climate sample data to enable the input and output data to sustain at the steep sector of the sigmoidal transfer function, increase the forecasting precision, and strengthen the effectiveness of the data recognition (Zime 2014).

In essence, it is essential to conduct the normalization of the input data to ensure that they are in an identical range of applied transfer functions. It was to restrict their range within the interval of 0–1 (Polo et al. 2015) because the middle layer's processing elements (P.E.s) were allotted a sigmoidal activation function. As a result, the shape of this function is critical to the ANN's learning. The weight

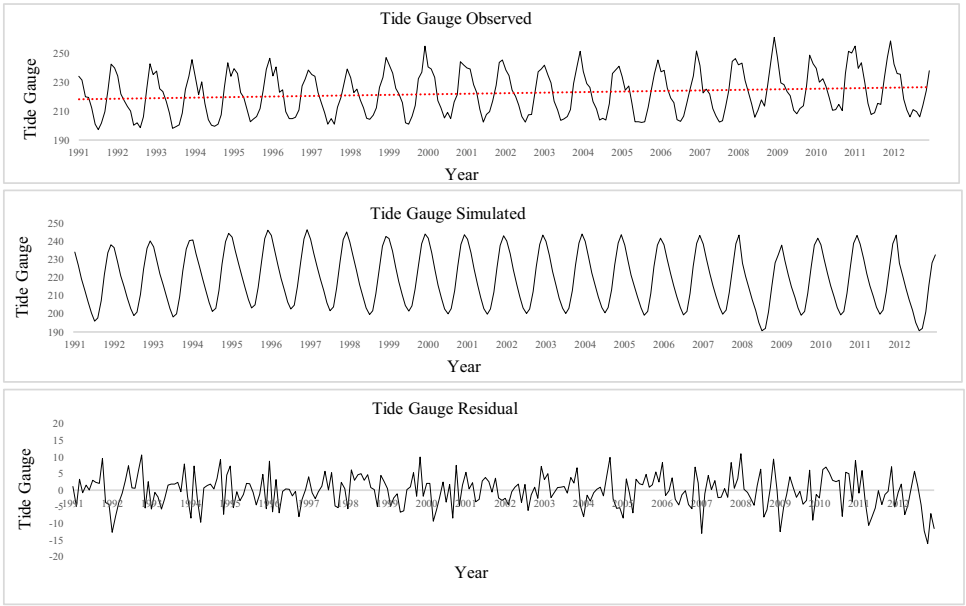

Fig. 1 Observed, simulated, and residual time series data of Chendering station

variation close to a value of 0 or 1 is minimal P.E. and "dull," while those closer to 0.5 react more (Ghamarnia and Jalili 2015). Thus, the following formula was used to normalize the data (Eq. 1):

$$X_{normal} = 0.5 + 0.5\left(\frac{x - x_{mean}}{x_{max} - x_{min}}\right) \quad (1)$$

where x_{normal} is the normal data, x_{mean} is the observed data means, x_{min} is the minimum, and x_{max} is the maximum observed data. In this study, five input and one output data for the ANN structure were used for simulation (from 1991–2012) and prediction (2013–2020).

NARX model procedure

The methodological framework used to address the study's first objective is depicted in Fig. 2. It displays the necessary steps as well as the necessary data for each stage. The methodology is divided into data analysis and applying the NARX model. After using statistical procedures to normalize and replace missing data, the data was used to train the neural network model. Finally, the study uses the NARX model to select the best model performance for accurate prediction. The NARX model uses five inputs and one output.

MLP network

This research pre-processed normalized calibration data (Zhao et al. 2012). Rumelhart et al. (1986) opined that the Back Propagation (BP) algorithm represents a superlative and well-known case of the Multi-Layer Perceptron (MLP) training algorithm that represents one of the best widespread techniques. The approaches optimize the feed-forward neural network training. Polo et al. (2015) noted that BP refers to a learning device that resolves predictions in multi-layer perceptron networks, which requires differentiability in the output layers' activation function.There

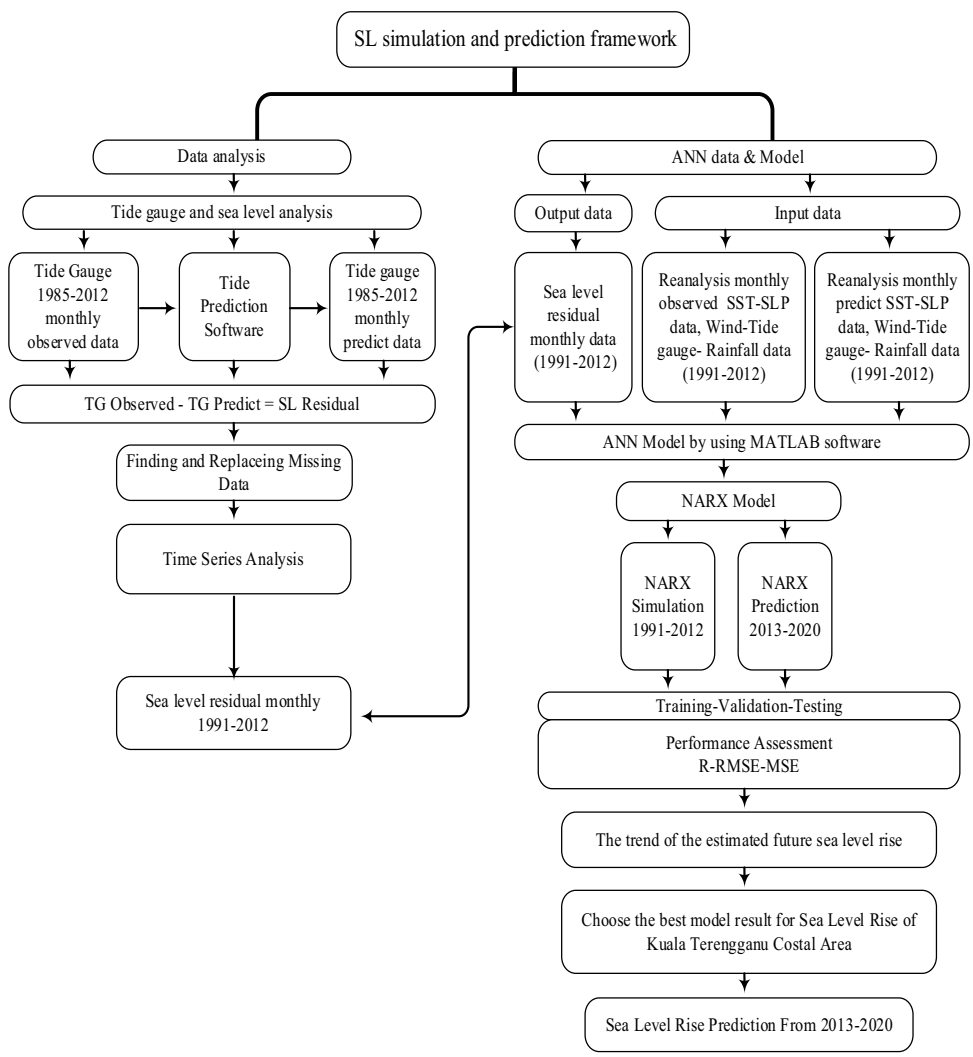

Fig. 2 Sea-level change analysis and prediction framework

are two steps involved in the BP neural network training, namely, forward and backward steps. The forward step necessitates the propagation of the input signals from the network input to the output. In contrast, the backward step entails the backward propagation of the calculated error signals through the network, which is utilized to adjust the weights (Tsoukalas and Uhrig 1996). Thus, forward and backward steps concerning all training sets would be repeated until the error is reasonably low (Polo et al. 2015). Therefore, the best architecture model is determined by comparing the performance of the calibrated model (Zhao et al. 2012). The algorithm modifies the weights of every connection to reduce the error. After repeating this procedure for a sufficient number of training cycles (epochs), the network will generally converge to a state with a network error more petite than a specified threshold. As a result, the network has been trained. The traditional BP computes relatively slowly due to linear convergence.As a result, the current study employs a recent second-order algorithm (the Levenberg–Marquardt Algorithm (LMA)), which speeds up the process of addressing several problems at the expense of more excellent computational memory (Levenberg 1944). The entire dataset would be divided into three categories to achieve perfect model generalization: validation, training, and testing. After training the MLP network, the training dataset is used to fine-tune the bias and weights, while the validation set is used to halt training to avoid poor generalization. Finally, Hadzima-Nyarko et al. (2014) use the testing set to figure out how good the trained MLP network is.

NARX model

Xie et al. (2009) posited that the nonlinear autoregressive network, which has exogenous inputs (NARX) model, is frequently utilized in the identification area system. As a neural time-series device, the NARX is a recurrent dynamic network with feedback connections that encompass some network layers. Thus, the NARX model is centered on the linear A.R.X. model, which is generally used in time-series modeling.

The NARX model's defining equation is given as follows:

$$y(t) = f(y(t-1), y(t-2), \ldots, y(t-n_y), u(t-1), u(t-2) \ldots, u(t-n_u)) \quad (2)$$

It indicates that the next value of the dependent output signal y(t) is regressed on the previous values of the output signal and previous values of an independent input signal. Hence, the NARX model can be executed using a feed-forward neural network to estimate the function (f). The resulting network is displayed in the diagram below with a two-layer F.F. network for the approximation (Boussaada et al. 2018; Li et al. 2019; Al-allaf et al. 2011).

Figure 3 illustrates the input and output of the NARX model, whose design is based on a distinctive multi-layer perceptron, neurons with modifiable synaptic bias and weights. Hence, the present and past values of the input that connote the independent inputs created from outside the network and the delayed output values on which the model output is regressed signify the signal vector's data window utilized in the input layer. The learning device multi-layer perceptron networks require a resolution heuristic algorithm that ensures the most excellent solution. For example, Polo et al. (2015) noted that the Levennberg-Marquardt algorithm trained the network in the MATLAB software.

Diverse applications of the NARX network exist. It can be used to predict the subsequent input signal's value. It can also be used for nonlinear filtering where the target output is the input signal's noise-free version. The NARX network's output is an estimate of nonlinear dynamic systems that are being modeled. As part of a typical NARX architecture, the output is returned to the input of the feed-forward neural network. It could create a series–parallel architecture in which the accurate output is used rather than feeding back the estimated output.

Numerous researchers have applied the statistical analysis of tide gauges to predict sea-level change in the Kuala Terengganu shoreline area (Zhang et al. 2004; Garcin et al. 2013). However, alternative meshless Artificial Intelligence (AI) methods, namely ANNs, fuzzy logic, and Nero-Fuzzy, can be utilized to address issues affecting nearshore

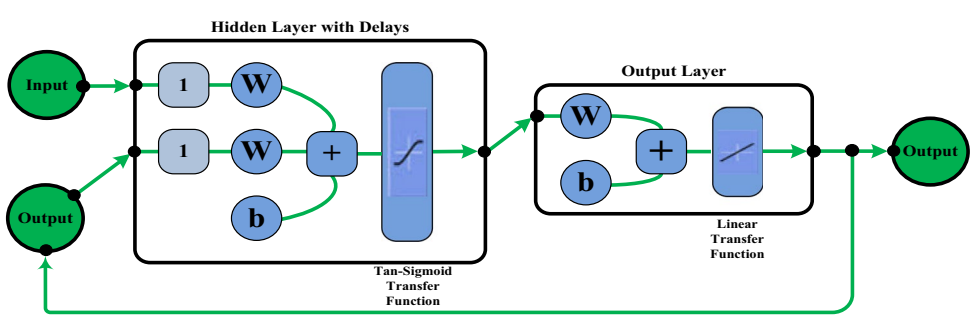

Fig. 3 A snapshot of the NARX network model

sea-level change predictions. The initial development of ANNs started in the 1940s (McCulloch and Pitts 1943), followed by continuous development, primarily through the efforts of Hopfield (1982) and his works on iterative auto-associable neural networks (Hung et al. 2008). In recent decades, ANN has found a more significant practical application because of the developed algorithms that overcome the limitations discovered in the early networks. Thus, many neural network models have been investigated, studied, and directed to resolve diverse sets of difficulties based on neural network structure and the learning algorithm (Hung et al. 2008).ANNs have been applied extensively in diverse environmental modeling, geoscience, data validation, and risk management fields to overcome the difficulty of new nonlinear statistical approaches (Napolitano et al. 2010). Neural networks are generally used to model various nonlinear relations between inputs and outputs and have recently offered alternative techniques for predictions, including forecasting rainfall-runoff (Hsu et al. 1995; Shamseldin 1997), river flooding (Campolo et al. 1997), rainfall intensity (Hung et al. 2008; French et al. 1992), streamflow (Zealand et al. 1999; Campolo and Soldati 1999; Abrahart and See 2000), wave parameter simulations (Deo and Naidu 1999), mixed tides (Lee and Jeng 2002), and for the now-casting of semidiurnal and diurnal tides (Tsai and Lee 1999) and related coastal studies (Makarynskyy et al. 2004).

In theory, an ANN possesses many advantages compared to other standard statistical methods. Neural networks automatically permit indiscriminate nonlinear relationships between the dependent and independent variables and all potential interactions between the dependent variables. Conversely, conventional statistical methods necessitate supplementary modeling to tolerate this flexibility. Moreover, ANNs do not have obvious distributional assumptions (Sargent 2001). For instance, ANNs that can estimate nonlinear mathematical functions (Hornik 1993) permit possible simulations of complex behavior of systems, behavior with no prior knowledge of the internal relationships among their constituents (Haykin 1999). The ability to generalize remains one significant advantage of neural networks. Hence, ANN models can learn the performance of a specific task based on the empirical data available. One key feature of these models includes the innovative information processing system structure. The distinctive advantage of ANNs relative to other methods is the self-learning capacity that enhances their ability to specify the essential connection between the input and output variables without requiring prior knowledge of the nature of the association. Zhao et al. (2012) noted that this advantage makes ANNs suitable for complex nonlinear problems that cannot be analytically resolved. This advantage makes the ANN models superior to other traditional statistical models, such as the Multiple Linear Regression (MLR) models, which are inappropriate for non-normally distributed data (Masters 1993).

Another merit of ANN is its capacity to resolve specific problems. ANN models are organized in many interconnected processing neurons or nodes that work in unity. Therefore, they can be powerful tools for modeling (Lek et al. 1996; Lek and Guégan 1999; Mas et al. 2004). Additionally, ANN can learn from their surroundings using diverse samples in their learning algorithms. Every time an ANN is generalized, it can connect the input data even if it did not utilize them at the learning stage (Hornik et al. 1989). The weights in the ANN are adjustable and can interrelate and react to the setting. Therefore, the ANN can respond adequately to situational changes and self-retrain after the initial training session concludes (Fredrick and Kostanic 2001).

One major weakness of an ANN is the quality of its "black box." In other words, it is difficult or sometimes impossible to understand a problem using an ANN model without applying additional effort. For instance, regression techniques can remove potential explanatory variables that do not add to the fit of the model. Moreover, the regression technique centered on the fundamental statistical theory permits the testing of a hypothesis concerning the multivariate and univariate relationship between the outcome of interest and every explanatory variable. In ANN models, however, these characteristics are typically unavailable.

Further current shortcomings of ANN are the computational resources needed and the lack of standard software (Sargent 2001). They are also not easy to calculate and present the odds ratios and standardized coefficients corresponding to every variable, unlike regression models. Similarly, the weights generated by a neural network analysis are challenging to interpret because they are influenced by the program utilized to generate them (Baxt 1995). It raises the issue of interpretability for an individual variable. Figure 4 illustrates the levels (predictors) that constitute one of the significant characteristics criticized in neural network models (Ohno and Rowland 1999).

The NARX network offers another essential application, namely, the modeling of nonlinear dynamic systems. The output of the NARX network can be considered an estimate of the output of a nonlinear dynamic system used for modeling. The output is the feedback to the input of the feed-forward neural network and forms part of the standard NARX

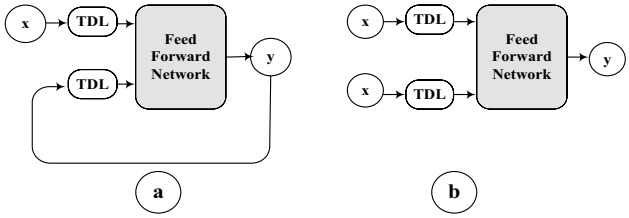

Fig. 4 Architectures of the NARX. **a** Parallel. **b** Series–parallel

architecture. Because the accurate output is available during the training of the network, one can create a series–parallel architecture, in which the accurate output is used instead of feeding back the estimated output.

It has two advantages. The first is that the input to the feed-forward network is more accurate. The second is that the resulting network has a purely feed-forward architecture, and static backpropagation can be used for training. In this study, during the training phase, the series–parallel architecture is used because of the availability of the valid past values of the time series. The use of a series–parallel architecture has two advantages. The first is using valid values as the input of the feed-forward network. The second advantage consists of the architecture of the resulting network, which is purely feed-forward. The standard training algorithms for MLP networks can be used. After the training phase, the NARXis converted to a parallel architecture which is beneficial for a multi-step-ahead prediction. The mapping function F (·) is initially unknown and is approximated during the training process of the prediction. In the NARX model, the internal architecture that performs this approximation is the MLP. The MLP offers a robust structure that allows learning any continuous nonlinear mapping. As presented in Fig. 5, a classic MLP consists of three layers: the input, hidden, and output layers. Other elements consist of neurons, activation functions, and weights. The direction of the information flow throughout the layers is from the input to the output layer.

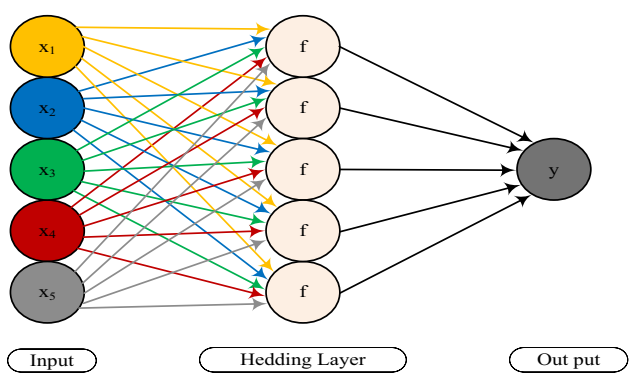

Fig. 5 A classic MLP neural network

In the NARX model, the internal architecture that performs this approximation is the MLP. The MLP offers a robust structure that allows learning any type of continuous nonlinear mapping. The direction of the information flow throughout the layers runs from the input to the output layer. For example, the previous layer gives the input vector *xj*, and its weight vector w_{ij} generates the scalar product $x_j \times w_{ij}$ (Fig. 6). An activation function *f* is then performed to obtain the following neuron output:

$$y_i = f\left(\sum_{j=1}^{n} x_j . w_{ij}\right) \tag{3}$$

where *i* is the index of the neuron in the layer, and *j* represents the input index in the ANN.

Evaluation and performance assessment

The performance assessment is discussed the prediction error, explaining the validation between the observed and predicted or simulated data. The evaluation of model accuracy is essential to determine the superlative neural network architecture that produces the most precise and reliable simulated or predicted data (Khamis and Abdullah 2014).

Several methods of performance assessment are applied to measure accuracy. This present study evaluates the performance of the Mean Square Error (*MSE*) and the coefficient of determination (*R*). *R* measures the goodness of fit of the regression. Here it is used as a measure to appraise the degree of correlation between the trained network estimation and the experimental data (Farajzadeh et al. 2014; Hamzehie et al. 2014; Mohammed et al. 2013; Hadzima-Nyarko et al. 2014; Nitsure et al. 2014; Mashaly et al. 2015; Ranković et al. 2014; Tezel and Buyukyildiz 2016). The correlation of determination (*R*) is given as follows:

Fig. 6 Details of a neuron

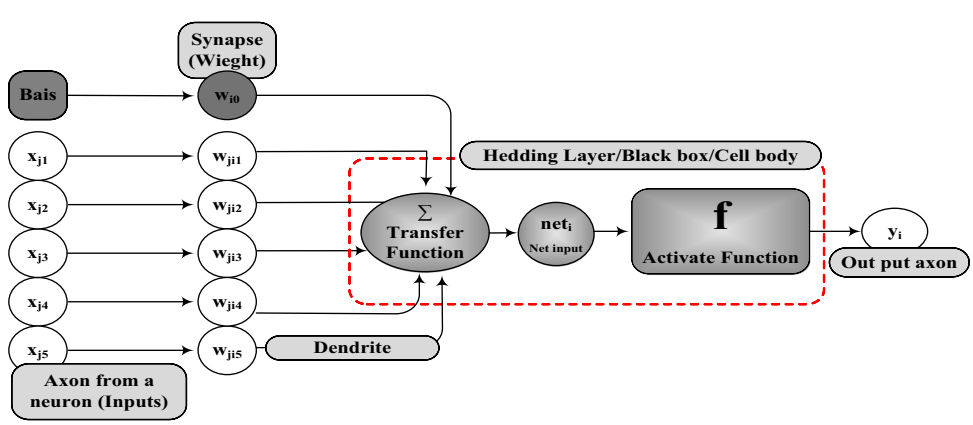

Table 2 Performance indicators of the various models on the test dataset

Statistic methods	*R*	*RMSE*	*MSE*	*MAPE*	*MPE*
Moving average method	0.79	8.090	53.613	0.917	0.018
Exponential method	0.79	7.585	57.968	2.489	−0.098
Holt-Winters method	0.73	8.628	74.868	2.856	−0.082
Fourier proportion	0.95	3.343	12.211	1.059	−0.026

$$R = \frac{\sum_{i=1}^{n}\left(O_i = \overline{O}\right)\left(P_i - \overline{P}\right)}{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2\sqrt{\sum_{i=1}^{n}\left(P_i - \overline{P}\right)^2}} \quad (4)$$

where n represents the number of samples, O_i represents the observed sea level, P_i represents the predicted sea level, $\overline{O}$ represents the mean of observed values, and $\overline{P}$ represents the mean of predicted values. The R values lie between 0 and 1, with the value of 0 indicating the absence of a correlation between observation and prediction values. In contrast, the value of 1 signifies a maximum correlation between the values.

Hadzima-Nyarko et al. (2014) posited that the Mean Squared Error (*MSE*) is commonly used to designate the network error. The *MSE* is an alternative procedure for measuring performance by considering the real values and an estimator (Leahy et al. 2008; Polo et al. 2015; Mohammed et al. 2013; Ranković et al. 2014).

It is given as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2 \quad (5)$$

A Mean Square Error (*MSE*) close to 0 indicates more accurate model responses.

Statistical smoothing models and remissing sea-level data

This section presents the empirical results obtained from the analysis of sea-level time series, which is the first objective of this study (Table 2). The ANNs simulated the sea-level rise between 1991 and 2012 and predicted sea-level rise for the years from 2013 to 2020 for Kuala Terengganu using the NARX model. The measurements collected over the past 22 years from a single tide gauge at the Chendering station were used to train and validate the employed neural network models. The study applied data accumulated over 22 years from the Chendering station. However, the dataset contained several data gaps. These were identified for the following years: 1992, 1993, 1994, 1996, 1999, 2004, 2008, 2009, 2010, and 2012 (Table 3).

Table 3 Missing and outlier data of sea levels, as identified through the analysis

Year	Month	Day	Missing	Year	Month	Day	Out layer
1992	Nov	24–25	2	1993	Dec	22, 23	2
1993	Mar	17–19	3	1995	Jan	6	1
	Apr	1–16	16	1998	Dec	13	1
1994	Aug	28–31	4	1999	Dec	21, 22, 23	3
	Sept	1–6	6	2000	Nov	22	1
1996	Mar	16–31	16	2001	Dec	22, 23	2
	May	15–20	6		Feb	15	1
1999	Dec	21	1	2004	Mar	9	1
2004	Jan	9	1		Feb	11	1
2008	July	29–31	3		Jan	1, 2	2
	Aug	1–22	22	2005	Mar	6	1
	Dec	2, 12, 14–31	20		Nov	20, 21, 22, 23	4
2009	Oct	11	1		Dec	17, 18, 19	3
	Jan	1–13	13			22, 23, 24	3
2010	Sept	11–23	13	2006	Dec	17, 18	2
2012	Sept	17–30	19			20, 21, 22	3
	Oct	1–17	17	2009	Jan	14	1
Total					Nov	5	1
12	22	196	196			21–22	2
				2012	Jan	27	1
					Dec	25, 26	2
				Total			
				16	29	65	65

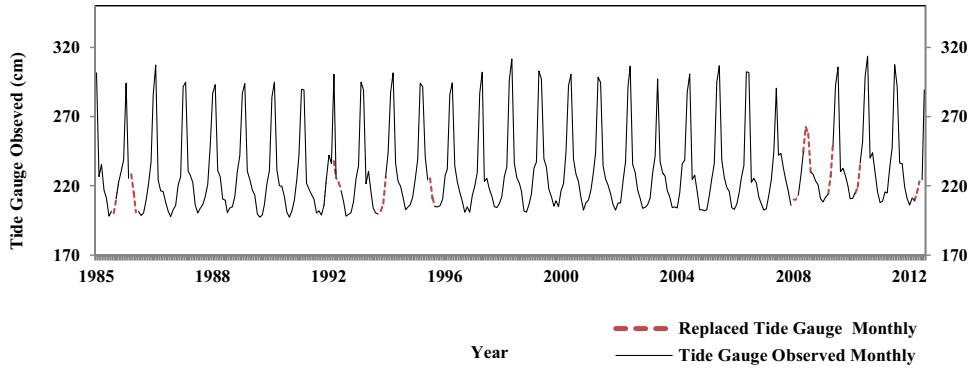

Fig. 7 Replaced missing tide gauge data using a moving average model

We chose various predicted statistical models in this section of the data analysis. First, we choose the model that best predicts results for tide data using *RMSE*, *MSE*, *RMSPE*, and *R*. We used some statistical models to simulate data from 1991-to 2012. After validation, the data replaced missing data with new data (Fig. 7).

This study reviewed numerous approaches to analyzing time-series data. Following the statistical modeling, obtaining observed tide gauge data, and analyzing bias descriptively, we found that all the time series data were non-parametric. For this type of data, we used non-parametric tests to identify patterns and the nature of the phenomenon represented in the observed data.

Sea-level simulation and prediction using the NARX model

The sea-level variations were simulated and predicted using the NARX model. The input used for simulation was the observed monthly tide gauge data, along with data on wind, rainfall (Kwan et al. 2014), SST, and SLP covering the time of 1991-to 2012. Thus, the SLR was the target output. Similarly, the input data for prediction included the predicted monthly tide gauge, and data on wind, rainfall, SST, and SLP. All data were from 1991 to 2012 due to the inherent limitations and insufficient data for some inputs. In the NARX model, five input data and one target (monthly data from 1991 to 2012) were used for simulation.

Similarly, for prediction, five inputs and one target (monthly data from 2013 to 2020) were used to train the neural network. Figure 8 shows the flowchart of the NARX model training process to predict future sea levels for the Kuala Terengganu. The sea-level rates between the layers were acquired by training the neural network through a reverse calculation process in which the contribution or importance of each effect criterion on sea level was computed.

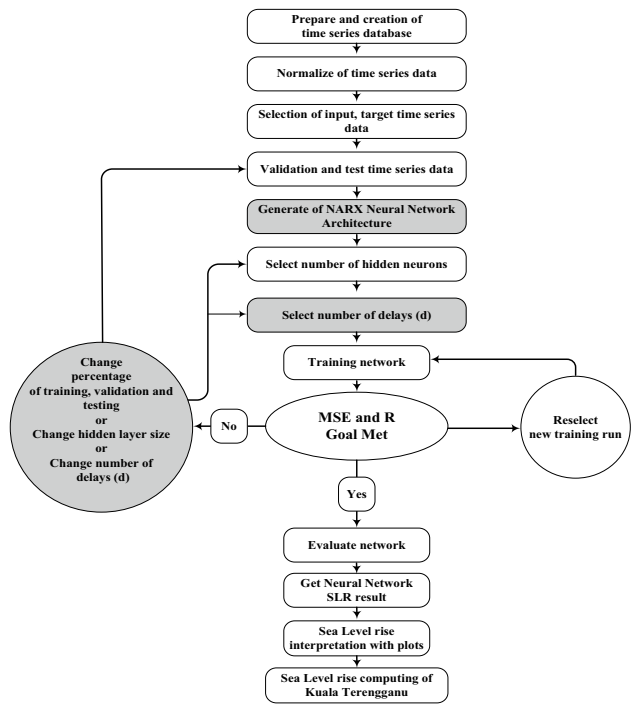

Fig. 8 Flowchart showing rates determination of future sea-level change using the NARX model

NARX-NN model architecture

The NARX model was trained, validated, and tested using 60%, 20%, and 20% of observed data. The model is run 250 times to achieve the best results. The best NARX model was chosen, with an architecture (5–6–1) and four delays (Fig. 9).

This model was selected as the best model with an *MSE* of 0.000292, 0.000269, and 0.000261 for the training set, the validation set, and the testing set, respectively, and their respective *R* of 93%, 92%, and 94% (Fig. 10a). Furthermore, under the best validation performance, the error

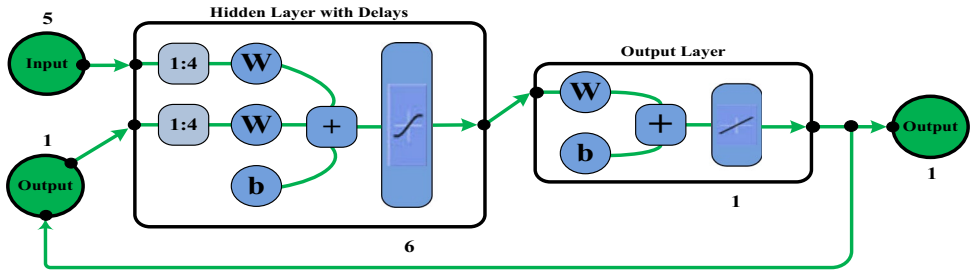

Fig. 9 NARX model architecture

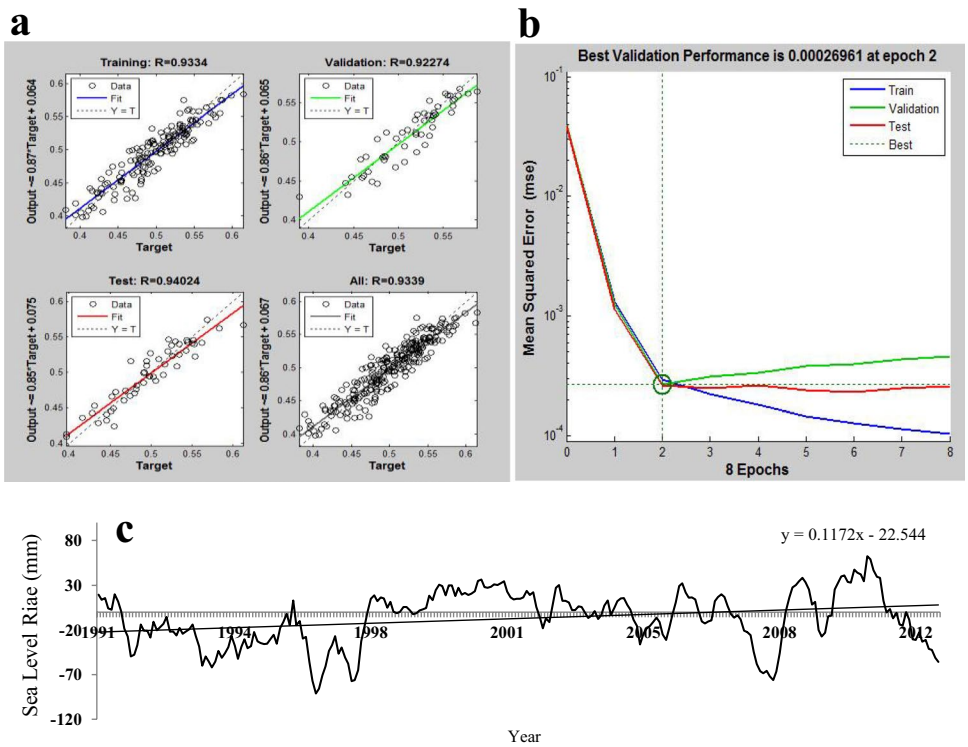

Fig. 10 Sea-level rise simulation trend determined with the NARX model

reached 0.00026961 at epoch 2 (Fig. 10b). Therefore, it indicates a good fit; therefore, the NARX model is well trained and can be used to simulate sea levels between 1991 and 2012. Figure 10c illustrates the result of the NARX model simulation that shows an upward trend for sea-level change in the Kuala Terengganu coastal area from 1991to 2012 with a maximum rate of 28.73 mm/year and an average of about 8.81 mm/year. Additionally, a falling sea level was noted at around 1.75–56.12 mm/year between 1991 and 2012. Based on this result, the NARX model with architecture (5–6-1) and four Lag is suitable for predicting the sea-level rise for 2013–2020.

Five inputs (predicted time series data), six hidden layers, and one output layer were applied to predict sea-level change based on the NARX model. This model used a similar approach of 60%, 20%, and 20% of data for the training, validation, and testing set. The model was run 250 times to find the best NARX model for predicting sea-level change from 2013 to 2020, and the most significant result came from an ANN architecture (5–6-1) with *MSE* and R. (Table 4) and (Fig. 11a).

Table 4 The simulation performance of the NARX-NN model after identifying the best result

	Training	Validation	Testing
R	97	96	89
MSE	0.00016	0.00049	0.00011

Figure 11b highlights that the best validation performance is at epoch 4, where the error reached 0.00049639. It indicates that the model is well trained and well fitted. Figure 11c shows an upward trend of the predicted sea level based on the simulated NARX model for 2013 to

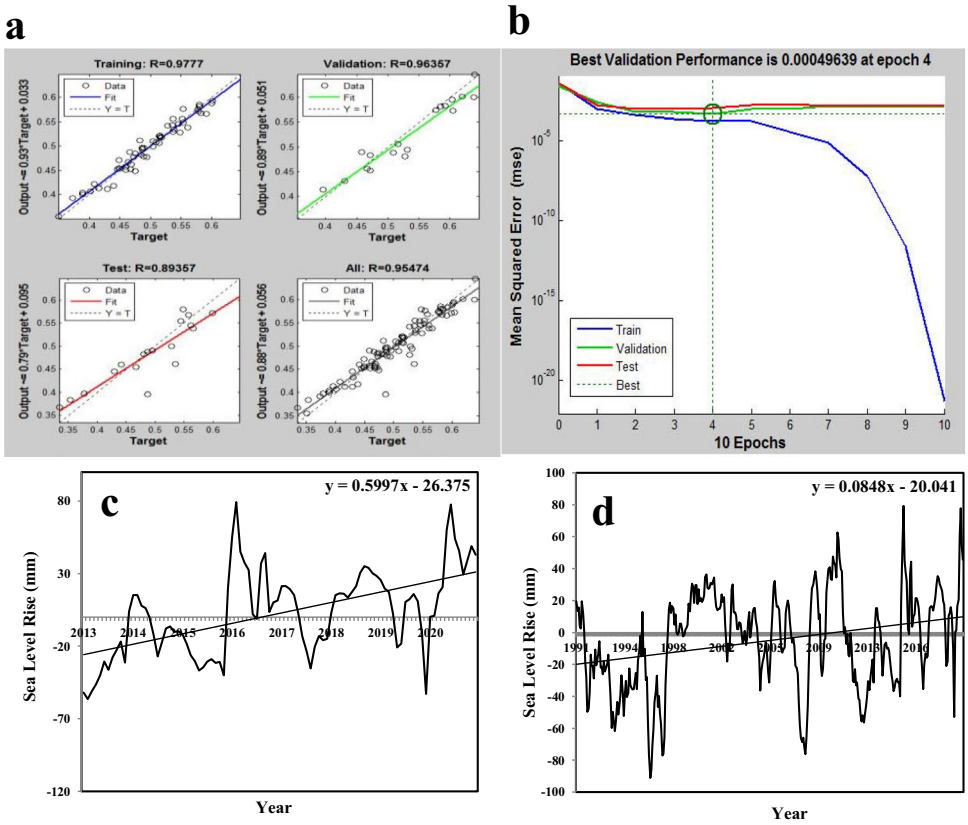

Fig. 11 **a** NARX model performance, training, validation, and the testing result (2013–2020). **b** The best validation performance using MSE. **c** Sea-level rise prediction trend using the NARX model. **d** Sea-level rise simulation and sea-level rise prediction trends (1991–2020)

2020. Figure 10d indicates the simulated and predicted sea-level rise between 1991 and 2020, which also shows an upward trend.

The study applied the prediction result of the NARX model with an architecture (5–6-1) and with four Lag to estimate the rate of sea-level change in Kuala Terengganu. The simulated and predicted sea-level changes from 1991 to 2020 based on the NARX model are shown in Fig. 12.

The result indicates an upward trend for sea-level change between 2013 and 2020, with a minimum increase of 1.10 mm/year and a maximum increase of 79.26 mm/year. Besides, the falling sea level was around 3.82–42.46 mm/year from 2013 to 2020. Changes in sea-level trends are associated with changes in input data, especially SST and SLP. There is a positive relationship between SST and sea-level change and a negative relationship between sea-level change and SLP (Bagheri et al. 2021a).

The results of this study's predicted sea level using the NARX model are consistent with the findings of Awang and Abd. Hamid (2013). N.A.H.R.I.M investigated the impact of climate change on sea-level rise in Malaysia. It is consistent with the findings of Awang and Abd. Hamid (2013). N.A.H.R.I.M. conducted a study on the impact of climate change on sea-level rise in Malaysia. The study projected

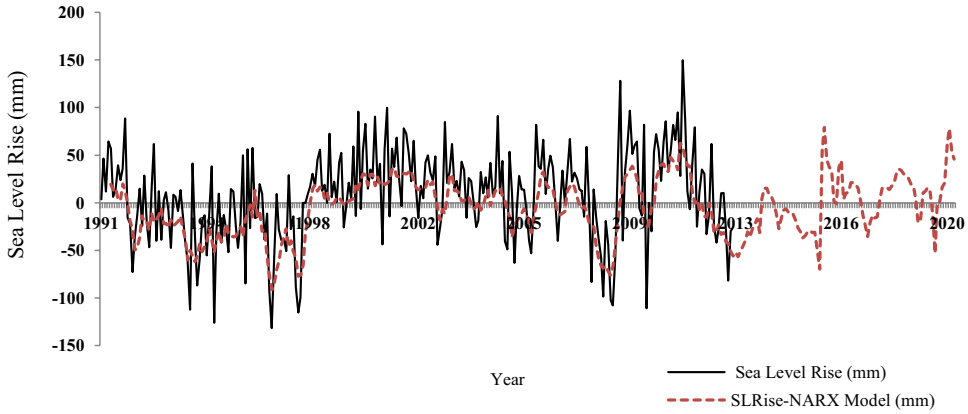

Fig. 12 Simulated and predicted sea-level rise by the NARX model (1991–2020)

sea-level rise on the Malaysian coast up to 2100, whereby the observed mean sea-level change rate based on satellite altimetry data from 1993 to 2010 is between 2.7 and 7.0 mm/year. The projected sea-level change for the year 2100 is 0.25–0.5 m, with the maximum value occurring in low-lying areas along the Northeast and West coasts of Peninsular Malaysia. The result of this study is consistent with the findings of (Awang and Hamid 2013; N.A.H.R.I.M. 2010a, 2010b; Bagheri et al. 2021c). Our findings indicate that Kuala Terengganu is expected to experience a sea-level rise which signifies potential hazards in the form of inundation, flood, and erosion.

Conclusion

Sea-level prediction data around shoreline areas is critical to accommodate sea-level changes. This study attempted to predict future sea-level changes in the shoreline area of Kuala Terengganu up to the year 2020 by applying a NARX model. After analyzing and normalizing sea-level observations (tide gauge data), sea-level changes in Kuala Terengganu were simulated utilizing a NARX model for the years between 1991 to 2012 and predicted for the years between 2013 and 2020. The simulation results show an upward trend from 1991 to 2012, with a maximum rate of 28.73 mm/year and an average of about 8.81 mm/year, and the prediction results show an upward trend from 2013 to 2020, with a maximum rate of 79.26 mm/year, and an average of about 25.34 mm/year. Between 1991 and 2020, sea levels in the Kuala Terengganu shoreline area increased at an average annual rate of 17.96 mm per year.

This study's findings align with previous research (Bagheri et al. 2021a; Makarynskyy, 2004). Investigated how climate change affects the sea-level rise in Malaysia and the predicted rise for Peninsular Malaysia (Bagheri et al. 2021b). Another study (N.A.H.R.I.M. 2010b) found that roughly 3.3% of the shoreline's 1963 km is highly susceptible. The most seriously affected low-lying Northeast and West coast parts of the peninsular were anticipated to receive 2.50–5.0 mm/year by year 2100. (Kelantan and Kedah). The study revealed a significant increase in sea-level rise in the past five years compared to 20 years ago. From 1993 to 2010, the observed average sea level along the Malaysian coast was anticipated to be between 2.7 and 7.0 mm/year (Din et al. 2019). These areas comprise the northern stretches of the Kedah beach and the southern stretches of the Terengganu beach. As a result, these estimates may be beneficial in warning residents in Kuala Terengganu's shoreline areas of the possibility of rapid sea-level rise, which could affect their livelihood and economy. As a result, the effects of rising sea levels on the country's population and socioeconomic well-being may be reduced.

The result may also forecast future hazard events in this area. Results showed that low-lying locations with significant human population density and socioeconomic activity are at risk of flooding, inundation, and shoreline erosion. The rising sea-level rates that we expect can help planning and implementation agencies and local governments develop plans and strategies for shoreline management in sensitive areas like Kuala Terengganu. This knowledge is critical, as the looming threat of a rising S.L. affects the socio-economy and quality of life of the residents of Kuala Terengganu. Armed with scientifically sound data, planners and decision-makers can establish plans to adapt to these potential changes.

Furthermore, the information gathered in this study can be used to determine Kuala Terengganu's erosion vulnerability. When developing vulnerability assessment systems for this region, this is essential. Overall, the study may improve the abilities of individuals involved in climate change planning, policy, and decision-making on shorelines and coastal areas. In addition, it will aid in the construction of long-term and short-term land use estimates that consider the shoreline area's possible vulnerability.

One of the most significant weaknesses of using ANN models is the lack of data and sources for environmental and meteorological parameters for shoreline modification in coastal areas. The lack of an essential quality database for the study area's environmental and climatic conditions. On-time series data, there were few documents and reports. As a result, we estimated quantitative data for environmental and climatic conditions. One of the most significant environmental and climate data issues was seeking and collecting data. They were gathered from various Malaysian departments and local authorities. Since this study has been conducted using limited shoreline, meteorological data, and tidal gauge stations in the future, it is evident that it can only provide a broad picture of coastal environmental vulnerability. However, a study of general coastal management and planning in the Kuala Terengganu shoreline area may point to future research directions.

According to the findings of this study, the research indicates the need for future research. This research suggests that combining the NARX model with climate data can simulate and predict sea level in the Kuala Terengganu coastal area. Our research employed this method to analyze a coastal city's susceptibility using various causal climate elements. Although the NARX model can show the potential of using this integration method and provide valuable results in the study area, more research and application of this methodology are needed to test the model's transferability in various factors with similar and different shoreline hazard conditions. In future studies, coastal environmental conservation can be combined with urban sustainability and vulnerability because hazards and vulnerabilities such as erosion and

flooding can affect coastal city sustainability. The geospatial model used in this study can help coastal city managers, planners, and developers identify threatened regions and improve the coastal land use and shoreline management plans. The future sustainability of coastal city systems can be forecasted using time series data and satellite images for the specified indicators, resulting in more accurate projected sustainability. As a result, decision-making information can be successfully extracted and used to assist government policy-making in developing more substantial more sustainable coastal city zones.

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Author contribution M.B., Z.Z.I.: methodology; M.B., Z.Z.I.: software; M.B., Z.Z.I.: validation; M.B., Z.Z.I.: formal analysis; M.B., Z.Z.I.: investigation; M.B., Z.Z.I., B.O.I.D.W: resources; M.B., Z.Z.I.: data curation; M.B., Z.Z.I.: writing—original draft preparation; M.F.A., W.I.A.W.T.: visualization; M.B., Z.Z.I.: supervision; M.B., Z.Z.I., A.B.P.: project administration; M.B., Z.Z.I., M.F.A.: funding acquisition; M.B., Z.Z.I., M.F.A., W.I.A.W.T., I.D.W.: supervision; B.O., I.D.W.: writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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