EnvironmentAsia
The international journal by the Thai Society of Higher Education Institutes on Environment

EnvironmentAsia 13(1) 2020 41-52
DOI 10.14456/ea.2020.4
ISSN 1906-1714; ONLINE ISSN: 2586-8861

Performance of Multi-Layer Perceptron-Neural Network versus Random Forest Regression for Sea Level Rise Prediction

Tika Olivia Bt Muslim[1]*, Ali Najah Ahmed[1, 2] and Marlinda Abdul Malek[1, 3]

[1] *Department of Civil Engineering, College of Engineering, Universiti Tenaga Nasional, Malaysia*
[2] *Institute of Energy Infrastructure (IEI), Universiti Tenaga Nasional, Malaysia*
[3] *Institute of Sustainable Energy (ISE), Universiti Tenaga Nasional, Malaysia*

*Corresponding author: tikaolivia20@yahoo.com
Received: July 13, 2018; 1st Revised: January 30, 2019; Accepted: September 26, 2019

Abstract

Sea Level Rise (SLR) is one of the most difficult elements to predict in the hydrological cycle. 12% of the area of Peninsular Malaysia, where the western low plains of muddy sediment are home to 2.5 million people, is vulnerable to flooding. In this study, two Artificial Intelligence (AI) techniques were used to predict SLR, namely, the Multi-Layer Perceptron Neural Network (MLP-NN) and Random Forest Regression (RFR) techniques. This studied, two cases were presented. The first case (Case 1) was to establish the prediction model for SLR by a monthly data set, while the second case (Case 2) was by means of a cyclical data set. From sensitivity analysis result, it was found that the most effective meteorological input parameters were rainfall (mm) and wind direction (degree). The performance of the models was evaluated according to three statistical indices in terms of the correlation coefficient (R), root mean square error (RMSE) and scatter index (SI). A comparison of the results of the MLP-NN and RFR showed that the MLP-NN performed better than the latter as the R obtained in Case 2 of the MLP-NN was 0.733 with 65.652 and 2.735 for RMSE and SI respectively. Meanwhile, accuracy improvement percentage (%AI) was 8%.

Keywords: Sea level; ANN; Multi-layer Perceptron Neural Network; Random Forest Regression

1. Introduction

During the 21st century, SLR is projected to have wide ranging effects on the coastal environment, development, and infrastructures. Consequently, there has been an increased focus on developing modelling or other analytical approaches to evaluate potential impacts so as to inform coastal management. It is, therefore, of major concern for climatologists to try to estimate changes in coastal sea levels that may be associated with climate change and global warming (Cui and Zorita, 1998).

A number of studies have shown that the rate of SLR has been increasing over the past decade (Ercan *et al.*, 2012). The rate of global SLR was faster during the period 1993 to 2003, at about 3.1 mm/year as compared to the average rate of 1.8 mm per year during the period 1961 to 2003 (IPCC, 2007), and was significantly higher than the average rate of increase of 0.1 to 0.2 mm/year recorded by geological data over the last 3,000 years. Sea levels are rising at a faster rate (Dasgupta and Meisner, 2009).

The combination of complex processes, including the forces of attraction of the Moon and the Sun on the Earth and combination of complex processes involving meteorological parameters like the atmospheric pressure, air temperature, water temperature, ocean currents, wind, etc. will produce variations in sea levels (Dasgupta and Meisner, 2009).

Winds are known to be one of the most important parameter for forcing sea level variability on the eastern margins of the ocean. The wind plays a role by moving warm water from one place to another. The future changes in the wind will have a strong effect on sea level in the Southern Ocean (Sturges and Douglas, 2011)

The impacts from rising sea levels have been acknowledged as having led to salt water interference, changes in surface water quality and groundwater characteristics, increased damage to life, property and coastal habitats due to flooding, impacts on agriculture and aquaculture through a decline in soil and water quality, and loss of tourism, recreation, and transportation functions. In general, it can be said that a range of potential physical, economic and social impacts will happen due to SLR in Malaysia (Nitsure *et al.*, 2014).

Many AI methods have been developed to improve water resources engineering in general and conventional hydrological methods in an efficient system. Due to studies related to the geosciences, such as ocean and coastal environments, Artificial Neural Networks (ANN) can be employed to predict sea levels (Rafiean and Aliei, 2013). There have been several studies in which neural networks were used to address sea level rise problems. (Nitsure *et al.*, 2014) applied three layers in the Feed Forward Error Back-Propagation type of Artificial Neural Network (FFBPNN) that was used for this work. This method is most commonly used in ocean-related studies to predict sea water levels by using hourly wind shear velocities at stations near the USA coastline. Similarly, (Makarynskyy *et al.*, 2004) applied the ANN to predict sea level variations at Hillary's Boat Harbour, Western Australia. (Piri and Khakha, 2016) applied the ANN with three most important variables that affect water levels at reservoirs, namely evaporation, wind speed and daily temperature, to predict water level fluctuations at the Chahnimeh Reservoir in Zabol. The literature offers some successful ANN applications in relation to SLR predictions because of their flexibility in fitting in random data and their relatively simple development.

The objective of this paper was to develop an SLR prediction model. Therefore, two AI techniques were used, namely, the MLP-NN and RFR. The results were compared with the prediction results of the MLP-NN and RFR, which can achieve a high level of accuracy. The performance of the developed model in the training and validation stages was statistically analysed.

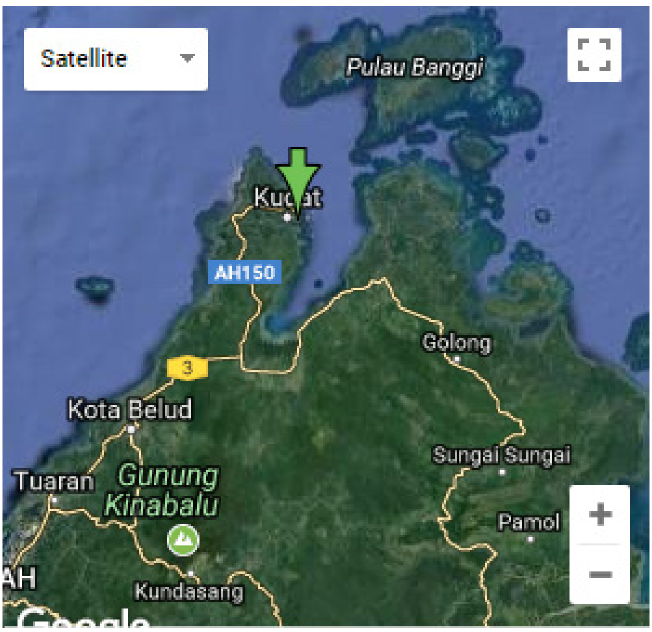


Figure 1. Map Showing the Location of the Study Area

2. Methods and Materials

2.1 Study Area

Kudat is an administrative division in the state of Sabah, Malaysia. It occupies the northern tip of Sabah. Its total area of 4,623 km² (6.3% of Sabah's total territory) makes it the smallest of the five divisions of Sabah. The coastal area of the Kudat station was used in this study. The location map of the station is provided in Figure 1.

2.2 Data Analysis

Two sets of data were prepared. The first included a record of the monthly mean sea level data from the tide gauge (2007-2016) that was obtained from the Permanent Service for Mean Sea Level (PSMSL) and can be accessed at http://www.psmsl.org/ (Figure 2). The second set of data was the meteorological input parameters. In the literature, various meteorological parameters were used to create a model for predicting SLR (Table 1).

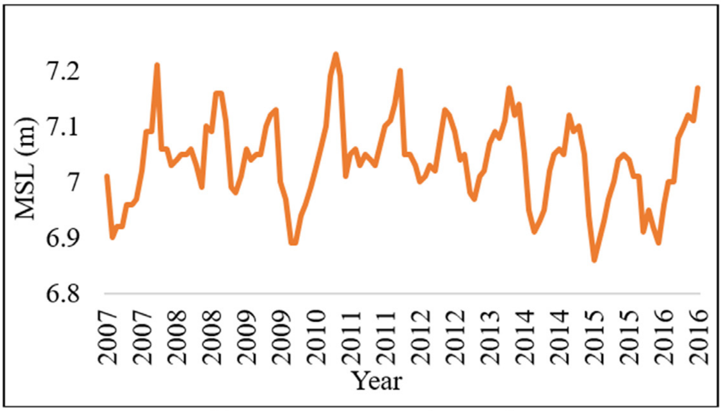


Figure 2. Monthly Mean Sea Level Data from 2007- 2016

Table 1. Meteorological Parameters Used in Previous Studies

Author(s) / Year	Meteorological Parameter	Location(s)
(Filippo *et al*., 2012)	Atmospheric preassure, Wind	Cananeia and Ilha Fiscal, Brazil
(Rafiean and Aliei, 2013).	Seal level pressure and Sea surface temperature	New York City coastal area
(Kisi *et al*., 2014)	Air temperature, Wind speed, Wind direction and Rainfall	Mukho Station, South Korea
(Nitsure *et al*., 2014)	Wind speed and Wind direction	USA
(Piri and Khakha, 2016)	Evaporation, Wind speed and Temperature	Zabol, Iran

Based on the literature, and existing measured values and statistical analyses, the following four meteorological parameters were selected as the second group of data for the MLP-NN modelling in this study, namely, rainfall (mm), cloud cover (oktas), wind direction (degrees) and wind speed (m/s). These meteorological parameters were monitored regularly each month over the period from January 2007 to December 2016, and were obtained from the Malaysian Meteorological Department (http://www.met.gov.my/).

In this study, the data were divided into two cases, namely, monthly data as Case 1 and cyclical data as Case 2. Each case was run with four different trials. Each trial had a different meterological parameter input. Table 2 shows the cases and the meteorological input divisions. Meanwhile, the analysed results of the study are given in Table 3. The coefficient of variation (CV) was employed to measure the statistical dispersion of the data, which is the mean normalized standard deviation of the given data set.

$$Cv\ (\%) = \frac{SD}{\text{Mean}} * 100 \quad (1)$$

All the parameters showed a coefficient of variation of between 2.14% and 64.75%. The lowest value was from the cloud cover parameter. The correlation coefficient (CC) between the SLR and the meteorological input parameter was calculated and presented in the same table.

2.3 Artificial Neural Networks (ANN)

ANNs are parallel information-processing systems (Nuratiah *et al.*, 2015). The internal architecture of ANNs is similar to the structure of a biological brain with a number of layers of fully-interconnected nodes or neurons (Nitsure *et al.*, 2012). MLP-NN with a back propagation training algorithm is the most widely used and it is organized as layers of computing elements known as neurons. Each neuron is connected to other neurons by means of direct communication links, each with an associated weight (Turban, 1992). During the learning process, the weights of the interconnections and the neural biases are adjusted through trial and error procedures to minimize errors (Buragohain, 2008). McCulloch and Pitt (1943) proposed the mathematical modelling of neurons shown in Figure 3.

The first is usually the calculation of the weighted sum of the inputs (Aj) by the following expression:

$$\sum_{i=1}^{n} w_{ij} + \theta_j \quad (2)$$

where w_{ij} = the weight between the *j*th neuron and the *i*th neuron in the preceding layer, and θ_j is the biased term of the *j*th neuron. The output of the *j*th neuron out of *j* is calculated with a sigmoid function

$$f(N_{etj}) = \frac{1}{1+e^{-Net_j}} \quad (3)$$

where, N_{etj} = the weighted sum of the *j* neuron for the input data.

Table 3. Basic Statistics of the Measured Meteorological Parameters

	Rainfall (mm)	Cloud Cover (octas)	Wind Direction (degree)	Wind Speed (m/s)
Mean	256.89	7.00	189.92	14.43
Min	85.20	6.48	10.00	9.10
Max	942.40	7.37	360.00	23.10
SD	166.34	0.15	91.42	2.91
CV	64.75	2.14	48.14	20.17
R	0.265	0.630	0.261	0.268

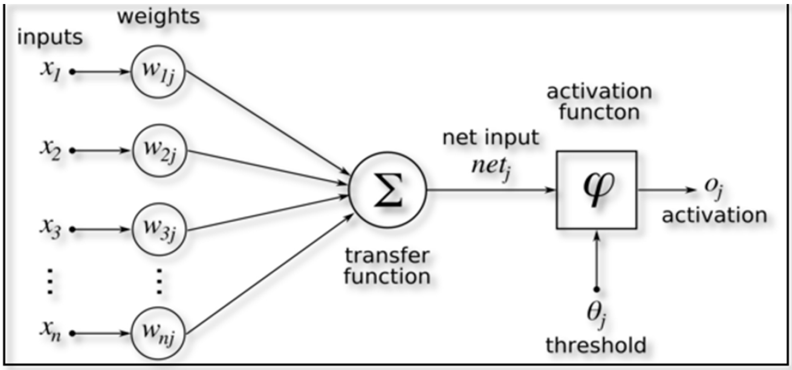


Figure 3. Mathematical Modelling of Neurons

2.4 Performance Criteria

The correlation coefficient (R) where x_i is the value observed at the time step, y_i is the value simulated at the same moment of time, $\bar{x}$ is the mean value of the observation, $\bar{y}$ is the mean value of the simulation and *n* is the number of time steps (Najah *et al.*, 2011).

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x})\cdot(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{4}$$

The root mean square error (RMSE) where y_i is the value simulated at the time.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}[y_i - yi^0]^2}{n}} \tag{5}$$

$$SI = \frac{\text{RMSE}}{\bar{x}} \tag{6}$$

The SI is the value of the division of the RMSE by the mean value of the observations.

3. Results And Discussion

3.1 Optimization of the Number of Hidden Neurons

Optimizing the number of hidden neurons to be used without a pre-set target for accuracy is one of the major challenges of neural networks (Liu *et al.*, 2012). A small number of neurons in the hidden layer may under-fit the data; subsequently the network may not be able to learn (Liu *et al.*, 2012). In this study, the optimum number of neurons was determined based on the minimum value of the Mean Square Error (MSE) of the training data set. The training was performed with a variation of 1-22 neurons. When a neuron was used, the value of the MSE was 531.61, and it decreased to 237.16 when 6 neurons were used. Thus, 6 neurons were selected as the best number of neurons. Enlarging the number of neurons to more than 19 did not significiantly decrease the MSE. Figure 4 shows the relationship between the number of neurons versus the MSE during training. The training and validation of the MLP-ANN were performed to minimize the MSE between the output and the desired response. Table 4 shows the connection of the number of hidden layers between the weighted value of the meteorological input parameters and the output layer.

3.2 Training and Validation of the Model

Figure 5 shows the proposed acrhitecture used to predict the MSL. The training and validation of the MLP-NN model were performed to minimize the MSE between the observed data and the predicted data. The performance goal was achieved randomly at 500 epochs.

3.3 Case 1

In Case 1, 120 data inputs were divided into two sets. The first part of the observations (January 2007-December 2014) was used for the independent training of the correcting networks, while the last portion (January 2015-December 2016) was used for the validation. Table 5 shows the validation in terms of the statistical test for each result, while Figure 6 shows the validation in terms of the graphical test for the five inputs so as to have better accuracy.

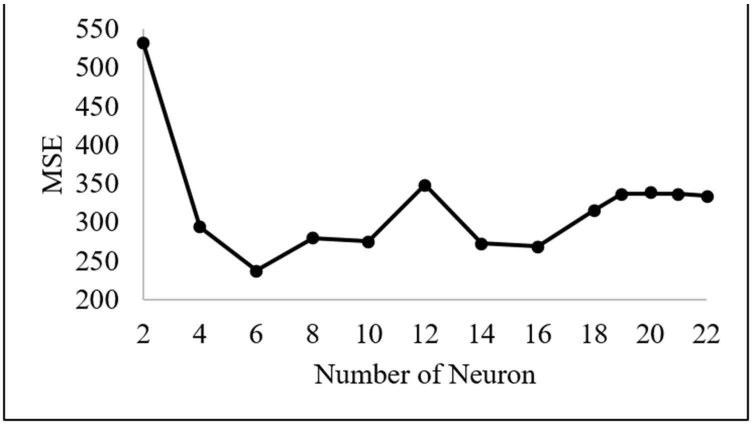


Figure 4. Relationship Between the Number of Neurons and **the MSE**

Table 4. Connection of the Hidden Layer Between the Weight for the Meteorological Input Parameters (W1) and the Output Layer (W2)

No	W1				W2
	Meteorological Input Parameters				**MSL**
	mm	**degree**	**m/s**	**octas**	
1	1.536	0.527	0.837	-0.338	-1.059
2	0.029	-0.023	-0.160	-0.292	0.036
3	0.462	0.174	-0.196	-0.031	-0.232
4	0.152	-0.118	-0.095	-9.069	0.088
5	0.828	-1.071	-0.542	-0.188	0.857
6	0.492	0.118	-0.131	-0.076	-0.217
7	0.304	-0.681	-0.237	0.069	0.509
8	0.096	-0.516	-0.076	0.124	0.435
9	0.037	-0.345	-0.063	0.079	0.313
10	1.715	0.573	1.075	-0.417	-1.252
11	0.430	0.208	-0.204	-0.221	-0.254
12	-0.13	-0.300	0.107	0.261	0.488
13	-1.50	-2.278	-0.075	-2.301	-1.872
14	0.258	-6.763	-0.166	-0.041	-0.046
15	0.390	0.127	-0.207	-0.083	-0.184
16	1.144	0.457	0.251	-0.090	-0.679
17	-0.910	-0.457	-0.934	-1.335	-1.172
18	0.063	-0.478	-0.059	0.138	0.430
19	0.537	-0.863	-0.371	-0.033	0.641

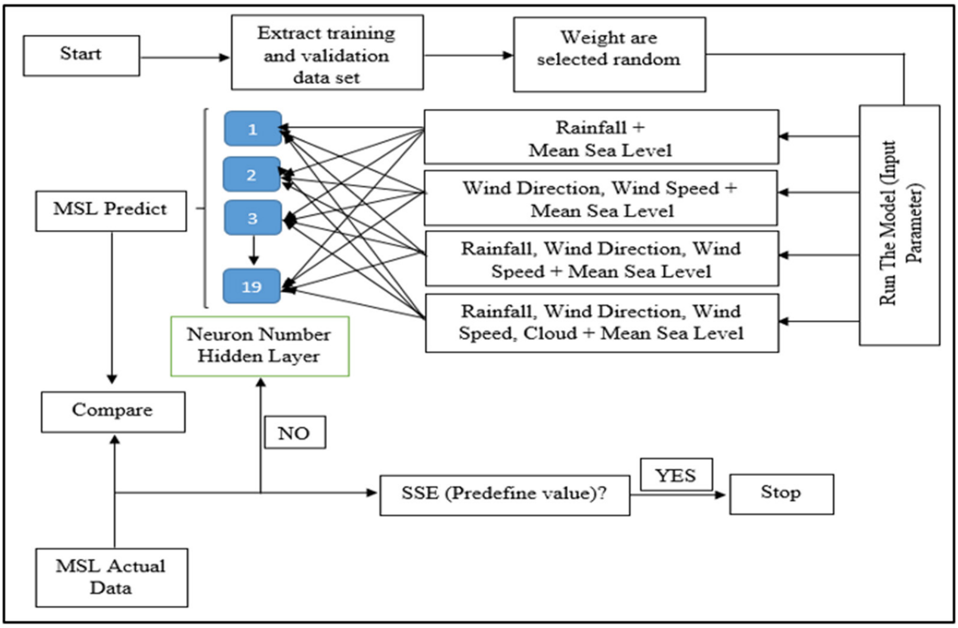


Figure 5. Architecture of ANN with Flowchart of the Procedure for the Algorithm.

Based on Table 5, by applying the five inputs, namely, rainfall, wind direction, wind speed, cloud and mean sea level, the output gave the best results in terms of R= 0.675 and RMSE=58.299, respectively in the running of the validation test compared to applying rainfall as a single input parameter, which gave a lower accuracy in terms of R= 0.134 and RMSE= 78.137 also during the running of the validation test.

Figure 6 shows the results of the validation in terms of a graphical test for the Mean Sea Level within the period 2007-2016 with four meteorological input parameters. During training, a high maximum value of 7.15 m was reached on December 2012, but the observed data was 7.20 m. Meanwhile, during the validation test, a higher maximum of 7.19 m was attained on December 2016, where the observed data was 7.17 m, which was achieved in 1.04 s.

Table 5. The Validation in Statistical Terms

		Performance Criteria		
Input	**Test Option**	**R**	**RMSE (m)**	**SI**
mm+ MSL (1:19:1)	Train Validate	0.246 0.134	78.890 78.137	0.657 0.651
degree, m/s + MSL (2:19:1)	Train Validate	0.286 0.149	78.405 79.905	0.653 0.666
mm, degree, m/s + MSL (3:19:1)	Train Validate	0.417 0.320	71.882 75.379	0.599 0.628
mm, degree, m/s, octas + MSL (2:19:1)	Train Validate	0.793 0.675	49.464 58.299	0.412 0.486

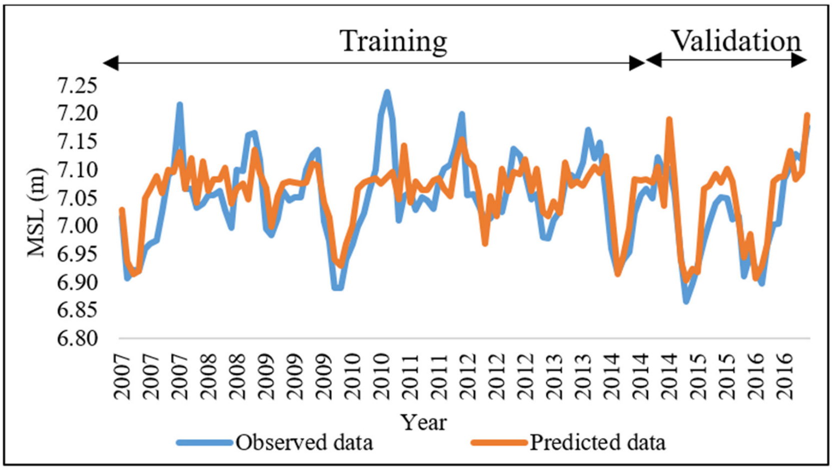


Figure 6. Validation in Terms of Graphical Test

3.4 Case 2

In Case 2, the first part of the observations (January 2007-Februari 2015) was used for the independent training of the correcting networks, while the last portion (March 2015-December 2016) was used for the validation. Table 6 shows the validation in terms of a statistical test for each result, while Figure 8 shows the validation in terms of a graphical test for the five inputs so as to have better accuracy.

Based on Table 6, by applying five inputs, gave best results in terms of R is 0.733 and RMSE is 65.652, respectively in running the validation compared to applying the rainfall as a single input parameter, which gave lower results which are R is 0.182 and RMSE is 69.426.

Figure 7 shows the validation results in terms of the graphical test for the Mean Sea Level within the period 2007-2016 with the cyclical data. During the training, a high maximum value of 7.13 m was reached from October 2007–Februari 2008 compared to the observed data, which was 7.10 m. Meanwhile, during the validation test, a higher maximum of 7.19 m was achieved on December 2016, where the observed data was 7.17 m, which took 0.25 s.

Table 6. The Validation in Statistical Terms

		Performance Criteria		
Input	**Test Option**	**R**	**RMSE (m)**	**SI**
mm+ MSL (1:19:1)	Train Validate	0.598 0.182	60.628 69.426	2.526 2.893
degree, m/s + MSL (2:19:1)	Train Validate	0.232 -0.533	63.638 121.51	2.652 5.063
mm, degree, m/s + MSL (3:19:1)	Train Validate	0.857 0.256	39.991 157.79	1.666 6.575
mm, degree, m/s, octas + MSL (2:19:1)	Train Validate	0.967 0.733	18.364 65.652	0.765 2.735

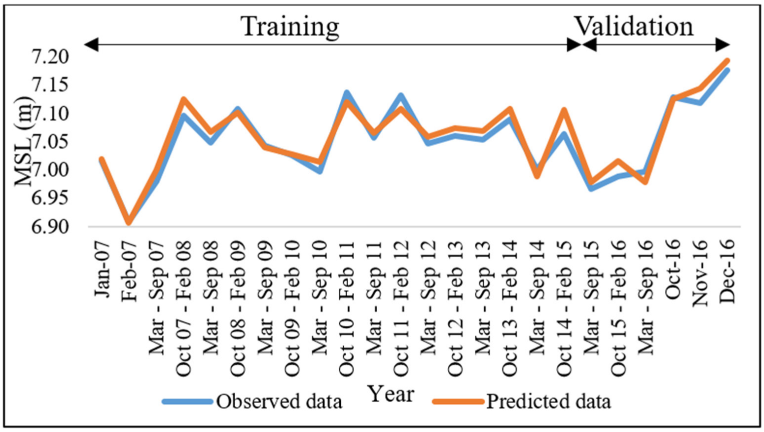


Figure 7. Validation in Terms of Graphical Test

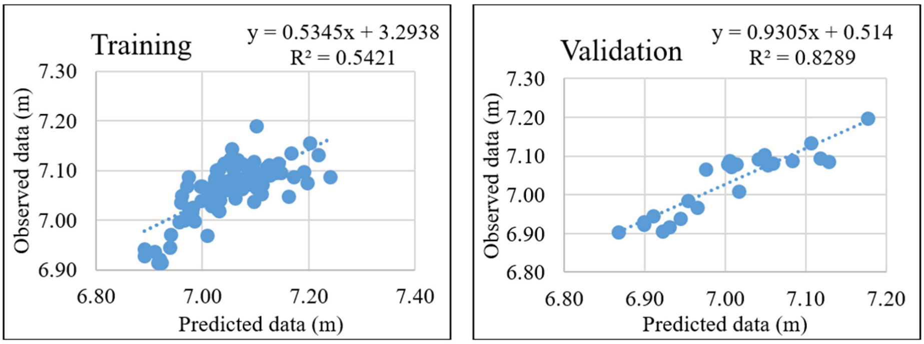


Figure 8. Scatter Plots Between the Observed Data and Predicted Data for Case 1

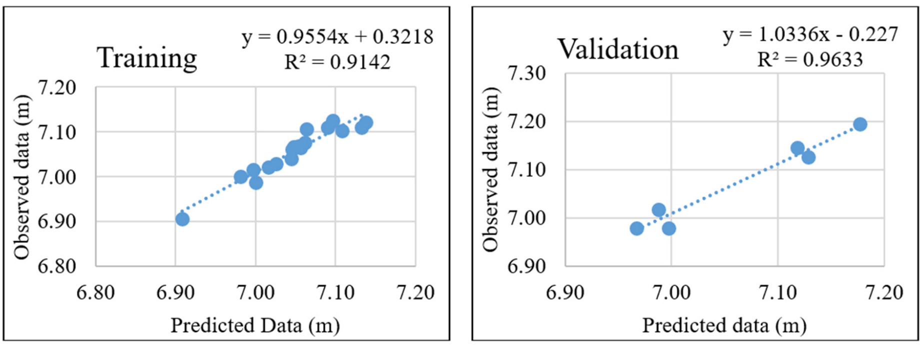


Figure 9. Scatter Plots Between the Observed Data and Predicted Data for Case 2

The model had to be verified when the predicted data and the observed data were close enough to satisfy the verification criteria. The scatter plots between the observed data and the predicted data for both cases are presented in Figure 8 and Figure 9. The comparison of Case 1 and Case 2 for the prediction of the SLR showed that the network output of Case 2 was able to depict the behaviour of the observed sea level data pattern more accurately than in Case 1.

It could be seen that the most predicted data were very close to the observed data. A value of R^2 should be close to 1, while an R^2 value of more than 0.9 indicates a very satisfactory performance, a value between 0.6-0.9 indicates a fairly good performance and values below 0.5 indicate unsatisfactory performance. In Case 2 the value of R^2 for the training and validation was more than 0.9, i.e. 0.9142 and 0.9633, respectively.

3.5 Random Forest Regression

RFR was devised by L. Breiman in the early 2000s. It is part of a list of the most successful methods that are currently available to handle the data in these cases and has been successful as a general-purpose classification and regression method (Biau and Scornet, 2016). Random forests for regression are formed by growing trees depending on a random vector Θ such that the tree predictor $h(x, \Theta)$ takes on numerical values as opposed to class labels. The output values are numerical, and it is assumed that the training set is independently drawn from the distribution of the random vector Y, X. The mean squared generalization error for any numerical predictor $h(x)$ is (Alahmadi and Kolmas, 2015).

$$EX,Y\,(Y-h(X))^2 \tag{7}$$

The random forest predictor is formed by taking the average over k of the trees $\{h(x,\Theta k)\}$. Similarly, for the classification case, the following holds:
Assume that for all Θ, $EY = EXh(X, \Theta)$. Then,

$$PE^*(forest) \leq \rho\, PE^*(tree) \tag{8}$$

Where ρ is the weighted correlation between the residuals $Y-h(X, \Theta)$ and $Y-h(X, \Theta')$ and Θ and Θ' are independent. Then,

$$PE^*(forest) =\rangle\ (E\,\Theta\, sd(\Theta))^2 \leq \rho\, PE^*(tree). \tag{9}$$

where $sd(\Theta) = \sqrt{E\mathbf{X},Y\,(Y-h(\mathbf{X}, \Theta))^2}$.

In this study, the RFR was used to compare the accuracy improvement AI index for the correlation coefficient statistical index to measure the significance of the proposed RF algorithms with MLP-NN. The AI was expressed as below.

$$\text{AI}\ (\%) = \left(\frac{RCase2-RCase1}{RCase2}\right) * 100 \tag{10}$$

Since the five input parameters gave the most accurate results in Case 2, therefore, the second algorithm had to be compared by proceeding with the five input parameters using the RFR algorithm. In this model, 100 was chosen as the number of trees because the more trees there are in the forest, the more robust will be the forest. In the same way, in the random forest classifier, the higher the number of trees in the forest, the more accurate will be the results (Ali *et al.*, 2012). Figure 10 shows the training and validation in terms of a graphical test, where the line graph does not fluctuate like the observed data but is just horizontal.

Table 7. A Summary of the Correlation Coefficient and AI for Case 1 and Case 2 in Both Models

	Case 1	Case 2	AI
	R	**R**	**R(%)**
MLP-NN	0.675	0.733	8
RF	0.230	0.305	24

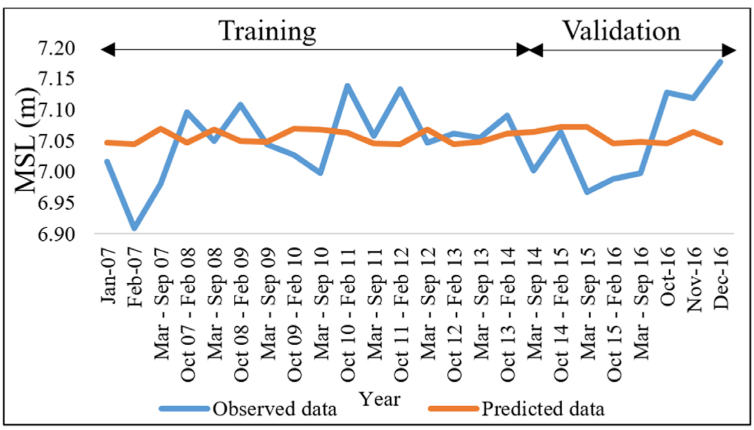
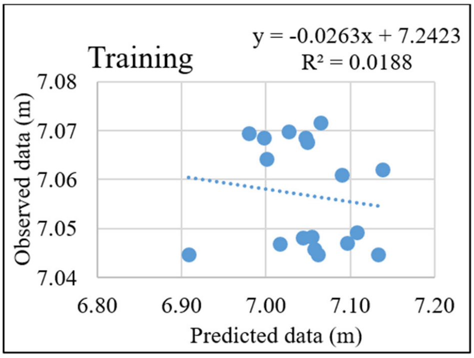


Figure 10. Validation in Terms of Graphical Test in Case 2.



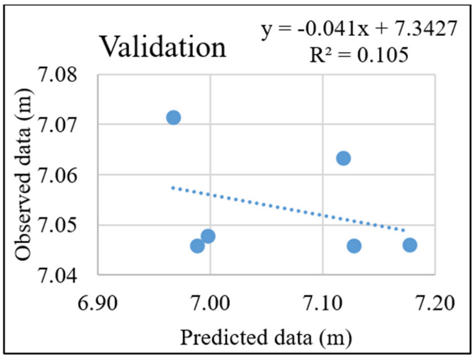


Figure 11. Scatter Plots Between the Observed Data and Predicted Data for Case 2

The maximum predicted data was 7.07 m compared to the observed data of 6.96 m from March 2015–September 2015. The scatter plots between the observed data and the predicted data for the RFR model are presented in Figure 11. It can be seen the values indicated unsatisfactory performance. From Table 7, it can be observed that by using the MLP-NN for both cases, a more adequate range of from 8% to 24% was obtained. The performance of the MLP-NN was outstanding, even in comparison to the RFR.

4. Conclussion

Based on sensitivity analysis result, it was found that the most effective meteorological input parameters were rainfall (mm) and wind direction (degree). During training and validation stage, the overall best performance was attained with case 2 where using cyclical data are further correlated with SLR. Based on this study, the best performing algorithm for the prediction of sea level rise is the MLP-NN. RFR algorithms have many advantages for the regression of complex crop systems, but they are not yet being widely used in this field. However, these algorithms are difficult to analyse, and the basic mathematical properties of even the original variant are still not well understood. The predicted values are not too high and even the time taken to run the model is much faster than the MLP-NN. A comparison of the results of the MLP-NN and RFR showed that the MLP-NN performed better than the latter as the ‘R’ obtained in Case 2 of the MLP-NN was 0.733 and the accuracy improvement percentage (AI%) was 8%. While, RFR obtained 0.305 and 24% for R and AI% respectively. Therefore, the MLP-NN is recommended to be used for sea level prediction. These predictions can be used for warning about probable high decrease and increase in sea level changes that can affect the life and economy of the coastal areas (Rafiean and Aliei, 2013). The present study used data from only one station, and further studies using more data from various areas may be required to reinforce the conclusions drawn from this study (Shiri *et al.*, 2013). The future extension of this project could follow multiple avenues. It would be interesting to try different algorithms, additional features or the model can be improved by a hybrid model to see if it is possible to create a better prediction. This will surely help various authorities to manage the possible damage that is expected to occur due to the impact of sea level rise in the future within the scope of the prediction of Water Resources Engineering in general and Hydrology, and for future works.

Acknowledgements

This research is supported by the Universiti Tenaga Nasional Research and Development Sdn. Bhd. (URND) under Seeding Fund U-TG-CR-18-03. The authors also would like to acknowledge the Universiti Tenaga Nasional for the financial support under Bold Grant 10289176/B/9/2017/14. The authors are grateful to Malaysian Meteorological Department (MetMalaysia) for providing data for this research.

References

Alahmadi M, Kolmas J. Estimating the effect of climate change on global and local sea level rise 2015; [Internet] http://cs229.stanford.edu/proj2015/346_poster.pdf

Ali J, Khan R, Maqsood I. Random forests and decision trees. IJCSI International Journal of Computer Science Issues 2012; 9(5): 272-278.

Biau G, Scornet, E. A random forest guided tour. TEST 2016; 25(2): 197-227.

Buragohain M. Adaptive network based fuzzy inference system (ANFIS) as a tool for system identification with special emphasis on training data minimization. [Thesis]. Guwahati: Department of Electronics and Communication Engineering, Indian Institute of Technology Guwahati; 2008.

Cui M, Zorita E. Analysis of the sea-level variability along the Chinese coast and estimation of the impact of a CO2-perturbed atmospheric circulation. Tellus A 1998; 50(3): 333-347.

Dasgupta S, Meisner C. Cimate change and sea level rise: A review of the scientific evidence. Environment Department Papers May 2009; (118): 1-36.

Ercan A, Bin Mohamad M, Kavvas M. The impact of climate change on sea level rise at Peninsular Malaysia and Sabah-Sarawak. Hydrological Processes 2012; 27(3): 367-377.

Filippo A, Rebelo Torres A, Kjerfve B, Monat A. Application of Artificial Neural Network (ANN) to improve forecasting of sea level. Ocean and Coastal Management 2012; 55: 101-110.

Kisi O, Karimi S, Shiri J, Makarynskyy O, Yoon H. Forecasting sea water levels at Mukho station, South Korea using soft computing techniques. The International Journal of Ocean and Climate Systems 2014; 5(4): 175-188.

Liu Y, Starzyk J, and Zhu Z. Optimizing number of hidden neurons in neural networks. [Thesis]. School of Electrical Engineering and Computer Science Ohio University; 2012.

Makarynskyy O, Makarynska D, Kuhn M, Featherstone W. Predicting sea level variations with artificial neural networks at Hillarys boat harbour, Western Australia. Estuarine, Coastal and Shelf Science 61 2004; (2): 351-360.

Najah A, El-Shafie A, Karim O, Jaafar O. Integrated versus isolated scenario for prediction dissolved oxygen at progression of water quality monitoring stations. Hydrology and Earth System Sciences Discussions 2011; 8(3): 6069-6112.

Nitsure S, Londhe S, Khare K. Prediction of sea water levels using wind information and soft computing techniques. Applied Ocean Research 2014; 47: 344-351.

Nitsure S, Londhe S, Khare K. Wave forecasts using wind information and genetic programming. Ocean Engineering 2012; 54: 61-69.

Nuratiah Z, Malek MA, Yusoff M. Application of computational intelligence methods in modelling river flow prediction: A review. In: 2015 International Conference. Preceeding on Computer, Communication, and Control Technology (I4CT 2015), 21 - 23 April 2015, Imperial Kuching Hotel, Kuching, Sarawak, Malaysia. Place of publication: IEEE; 2015. 370-374.

Piri J, Rezaei Kahkha M. Prediction of water level fluctuations of chahnimeh reservoirs in Zabol using ANN, ANFIS and Cuckoo optimization algorithm. Iranian Journal of Health, Safety and Environment 2016; 4(2): 706-715.

Rafiean H, Aliei M. Application of Neuro-Fuzzy Model for predicting sea level rise utilizing climatic signals: A case study. Technical Journal of Engineering and Applied Sciences 2013: 3825-3830.

Shiri J, Kisi O, Yoon H, Lee K, Hossein Nazemi A. Predicting groundwater level fluctuations with meteorological effect implications- A comparative study among soft computing techniques. Computers and Geosciences 2013; 56: 32-44.

Sturges W, Douglas B. Wind effects on estimates of sea level rise. Journal of Geophysical Research 2011; 116(6): 1-11.

Turban, E. Expert systems and applied artificial intelligence. New York: Macmillan Pub Co.; 1992.