The Efficiency of Neural Networks to Model and Predict Monthly Mean Sea Level from Short Spans Applied to Alexandria Tide Gauge

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Key words: Neural networks , mean sea level, Hydrography, modelling, prediction

SUMMARY

Traditionally, mean sea level MSL has been considered as a stable reference datum representing the vertical datum i.e. geoid. Recently it has been proven that sea level varies spatially due to sea surface topography and temporally due to changing of local and global meteorological conditions. The temporal variation known by sea level rise should be taken into consideration to study its effect on shoreline and consequently on the engineering works near shore. The proper determination of sea level rise can be done using the available monthly mean sea levels and the associated meteorological data. Unfortunately, in Egypt there are a few number of Tide gauges with continuous records, and even with tide gauges the data were interrupted by the war periods or other reasons. So, the available data for Egypt may be insufficient to the proper model of sea level rise using the traditional technique i.e. Least Squares. In this paper, The Neural Networks technique is suggested to model the short span mean sea level data compared to the Least squares. The monthly mean sea level associated with monthly meteorological data for seven years were considered. The Mean square error was estimated for each method of neural network and compared with the value computed using Least Squares technique. The methods of neural networks prove to be more effective in modelling and prediction of monthly mean sea level.

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1. INTRODUCTION

The sea level has played an important role in many of engineering and oceanographic aspects. It constitutes more than 70% of earth's surface. It is unstable surface due to many reasons, such as, tides and meteorological effects. If there were no tides and stable weather conditions, the seas and the oceans of the world would have a level surface, called mean sea level or vertical datum (Nassar, and El-Shaly 2000b). The mean sea level and other tidal datums are used for surveying and engineering purposes and to establish a system of tidal bench marks to which these datums can be referred, maintained, and recovered. For datum computation with the presence of tides and other non-tidal effects, the average heights of the sea measured every hour is determined for a specific period i.e. 19 years known by National Tidal Datum Epoch NTDE (NOAA Special Publication NOS CO-OPS 1 ,2000). NTDE is necessary for standardization because of periodic and apparent secular trends in sea level. NTDE includes all significant tidal periods, and it is long enough to average out the local meteorological effects on sea level, and by specifying the NTDE, uniformity is applied to all the tidal datums. However, because of relative sea level change, as the years pass, tidal datums become out of date for different purposes. Thus, a new NTDE must be considered periodically (Hicks, 1980).The continuous analysis of tide gauge readings, where the sea level readings taken, helps in detecting the temporal variation of sea level. Current estimates of global sea level rise are between 10 cm and 20 cm per century (Douglas, 1991 and 1992; NRC, 1990).

Recall, the mean sea level was thought to be a unique equipotential surface, i.e., represents the earth's actual gravity field. Accordingly, it was considered as the vertical realization of the geoid- that is, the surface that the sea would exist in the absence of oceanographic and meteorological dynamics. Historically, the geoid has played an important conceptual role in the vertical datum work. However, it is now well recognized that this assumption is not the case, and that the practical realization of the geoid, through the determination of MSL, is not in a uniform system and it varies from place to place due to dynamic effects resulting from existing oceanic circulation, wind and pressure patterns, and sea-water density differences that cause variations in the level of the sea surface with respect to the geoid. This variation is known by Sea Surface Topography SST (Vanicek, 1991). The Sea Surface Topography, or the spatial variations of MSL, is the departure of the mean sea level from the geoid. In addition, close to the shore, the seabed topography and river discharge also play a significant role in the presence of SST (Laskoeski, 1983).

Accordingly, the mean sea level as the most important tidal datum is not sufficient to define the geoid, i.e. the vertical datum without considering several factors affecting its variations

(Cross, 1952). On the other hand, the mean sea level is required for the purpose of determining the appropriate location of the engineering constructions and other activities relative to the local MSL along the coastlines, depending upon the adopted national specifications and regulations. The easy way to define the mean sea level, at any place, where no tide gauges are existing, is done through the traditional levelling procedure, through determining the height of the nearest ground Benchmark, which represents the elevation or depression of the point with respect to the geoid as the vertical datum approximated by the mean sea level. Anyhow, the vertical datum, determined through the levelling process, does not represent the mean sea level at any place or at any time (Nassar and El-Shazly, 2000a).

Furthermore, the variations of the sea levels represent one of the main factors affecting the design of the Coastal structures, and adopting the legal property line. Coastal engineering begins with a thorough description and understanding of the marine environment at the site of the proposed construction. The physical environment requires detailed knowledge of the site location and conditions, bathymetry, and knowledge of water levels and currents. The design height of most coastal and ocean structures requires knowledge of the height of Mean Low Water Level combined with the height of the astronomical tide, storm surge, and waves. The height of the highest and lowest observed tides relative to the engineering project datum is also valuable parameters.

The change in relative mean sea level may require that coastal engineers factor in effects of long-term sea level rise. Sea level change generally leads to increased shoreline erosion and wave overtopping, both factors contributing to failure of a structure. Sea level change may be accounted for in two ways. The first is to build the structure with the projected sea level change as a design consideration. The second is to build the structure less expensively, and to factor in the future cost of structure modification as required. On the other hand,tides and sea level changes have a controlling influence on many marine biological and geological processes. Changes of sea level over longer periods have important implications for coastal habitation and climate changes (Hannah, 1989).

Moreover, sea level variations as a consequence of global change put high demands on the prediction of future states of the shoreline, and hence on the understanding of very long-term scale of coastal change, spatial scale of kilometres, temporal scale of decades to centuries. The knowledge of future sea level heights in the nearshore environment is of great importance for protection of coastal and low-lying regions' residents, for monitoring and prediction of changes in complex marine ecosystems, harvest estimation for the fishery, as well as for planning and constructing coastal and offshore structures, and for the development and implementation of oceanbased alternative energy technologies .

In Egypt, the sea levels and the sea levels variations have affected many related applications. The mean sea level was established at Alexandria harbor in 1906 by taking the average of daily sea level for seven years (Cole, 1944). Various efforts have been done to monitor the sea level variations along Suez Canal and at some new established harbors, along both the Mediterranean and Red Seas, for the purpose of controlling the continuously increasing number of established new coastal constructions, as well as controlling the marine transportation. Along the coastlines of Egypt, which extend in the northern and eastern parts with total length around 2000km, different constructions and new development in various aspects have been taken place. Most of the new development requires the exact information about the adopted mean sea level at the place to build safe constructions. Such information also helps in defining the set back line of the constructions, the property line, and the foundation level for the structures from the coastline. The sea level data are available for the main tide gauge at Alexanderia harbour with published MSL recoerd from 1944 to 1988. The published records for tide gauges at Suez canal are from 1980 to 1987. Sea level data are also available for tide gauges at Marsa Matrouh and Al-Salum Cities at the nourthen coastl zone from 1969 to 1971. The distrbution of available tide gauges is given in Fig.1.

It is believed that the mean sea level at Alexandria has been changed from 1906 to now. Accordingly, it is necessary here to study the long term change of MSL at Alexandria to get an estimate for the variations of MSL along northern Egyptian coastline. The problem here is to advise a viable technique, which would enable us to use sea level records, derived from tide gauge observations, to model and predict sea level variations. Least squares technique may be used to model and predict the variation of MSL based on sufficient available data and strong mathematical model. With short span MSL data , the Neural networks method is suggested in this paper compared with least squares method. The available monthly mean sea level data at Alexanderia tide gauge are considered. The meteorological data for the period 1980 to 1987 at Alexanderia are taken into consideration.

2. MODELLING OF MEAN SEA LEVEL USING LEAST SQUARES TECHNIQUE

Recall that, one of the main sources of sea level variations is the long term changes. The magnitude of this long periodic variations, and the driving mechanisms behind it, are such that they have the potential not only to invalidate the MSL datums of many of the local height networks used in coastal development projects, but also to create significant problems for low-lying coastal communities over the next 100 years. The sources of sea level variations can be summarized as follows (Vaniĉek, 1978):

1. Atmospheric pressure variations.
2. Dynamic effects of sea level variations (currents).
3. Wind variations.
4. Atmospheric temperature variations.
5. Long periodic variations.
6. River discharge variations.
7. Changes in bathymetric configuration.
8. Glacial melt and crustal movements.

The suggested mathematical model to model and predict the possible variations of MSL is expressed as (Vaniĉek, 1978, and Anderson, 1978):

$$y(t_i) = a_1 + a_2 t_i + a_p \delta p(t_i) + a_T \delta T(t_i) + a_D \delta D(t_i) + a_{W_N} \delta W_N(t_i) + a_{W_E} \delta W_E(t_i) + \sum_{j=1}^{5} A_j \left(\cos \omega_j t_i - \varphi_j \right) \tag{1}$$

where: $y(t_i)$ is the observed MSL relative to the zero datum of the tide gauge at time t_i; a_1 is the datum bias; a_2 is the linear trend; and $a_P\delta P$, $a_T\delta T$, $a_D\delta D$, $a_{WE}\delta W_E$, and $a_{WN}\delta W_N$ are the contributions of the pressure variations δP, temperature variations δT, river discharge variationsδD, tangential wind speed δW_E, and normal to the shore wind speed variations δW_N. A_j, φ_j are the amplitude and phase of the periodic components with frequencies ω_j corresponding to the following five periods:

1. Annual (elliptic) tide with a period of 1 solar year.
2. Semiannual (declination) tide with a period of .5 solar year.
3. Lunar nodal tide with a period of 18.613 years.
4. Lunar perigee tide with a period of 8.847 years.
5. Chandler wave (oscillation of the Earth's poles) with a period of 435 solar days.

However usually for meaningful and reliable modeling of MSL, the span of observations should be as large as possible. It is well known, for a unique best estimation of unknown quantities from redundant observations, the least squares estimation process should be used (Mikhail, 1976). The final outcome of this process will be the set of unknown coefficients and concequently the modelled or predicted MSL. As long as the measured meteorological quantities are treated as observables, which represents the reality,and hence the so-called combined, general, or condition equations with parameters technique of least squares adjustment was applied (El-Shazly, 1995).

2.1 Data Used (Alexandria Tide Gauge)

The monthly mean sea level data at Alexandria along with the data of pressure, temperature, and wind speed in East and North directions for a period of 84 months were used in the above model i.e. Eq. 1. This period started from January 1980 to December 1986. We started with calculating the mean value of the given meteorological data. The differences from the mean values, i.e. δp ,δT ,δW_N, and δW_E were used in the above mathematical model.
However, the monthly discharge data were not available and hence they are not included in this analysis.

Monthly mean values of sea level at Alexandria were given from Permanent Service for Mean Sea Level (PSML). A summary of the main characteristics of mean sea level data for Alexandria is given in Table 1. The meteorological data were found to be available from the Egyptian Authority of Meteorological Observations. Of course, it was required to request all the available meteorological data (pressure, temperature, and wind) at Alexandria, for the same periods as the MSL data. However, such complete meteorological data set required, unfortunately, a bulky budget, which was surely beyond the available funds for the current research. Therefore, a sample from this data was chosen, on a compromise basis as shown in Table 2.

2.2 Application and Results of Least Squares

The method of general least squares was applied to model the sea level variations using Eq. 1, as mentioned before. This means that all meteorological quantities were treated as observables, in the process of least squares adjustment, which will receive some appropriate residuals after adjustment. The discharge contribution has been unmodeled for the monthly because of unavailable data (El-Shazly, 1995). Data size was only limited for 60 recorded and the other data were used to test the ability of the model to predict MSL. Compared to the original MSL, the results of the modelled monthly data are given in Fig. 2. The mean square error MSE is computed for this data and found to be 19 cm^2 .

3. ARTIFICIAL NEURAL NETWORK (BASIS)

The basic ideas and the motivation for the early developments of artificial neural networks ANN was the study of the structure and processes in human brain, which is in several aspects similar to ANN. They both have units called neurons which are interconnected. Similarly to human brain, ANN has to be taught or trained. There are two types of learning procedures: supervised in which questions and answers are known and ANN has to learn the correct answers, and unsupervised learning where the answers are not known (Stopar et al,).

The basis of a neural net is the concept of neuron considered as a unit. The unit takes the argument *n*, which can be formed as a sum of the weighted input and bias, and by means of the transfer (activation) function *f*, typically a step function or a sigmoid function, to produce the output. Note that there can be many input weight pairs to form the unique argument *nij* of the transfer function *f* in the *j*-th neuron (*i* is the number of input nodes, *j* is the number of neurons in the first hidden layer). Several such neurons can be combined in a layer, whereas a particular network can contain one or more interconnected layers of neurons. The pattern of these interconnections is called the architecture of the ANN.

Non-linear activation functions, such as a log sigmoid or a hyperbolic tangent sigmoid, for the hidden units are needed to make the ANN capable of representing non-linear dependencies. An activation function in the output neurons should suite the distribution of the target values. The method of determining the weights and biases is called learning. The learning process requires a set of patterns “input – target output”. During the learning process, the weights and the biases of a network are iteratively adjusted to minimize the network performance function. This urges the entire ANN to perform in some expected way. Each presentation of a training set to a net is called an epoch (Makarynskyy, O., et. Al 2004).

However, (ANNs), which are able to approximate any nonlinear mathematical functions allow reasonable simulations of complex systems’ behaviour without any preceding knowledge of the internal relations among their components provided that a reasonably large amount of data has been collected and taken into consideration. The ANN approach has been successfully used in many studies related to geosciences, such as ocean, coastal, environmental and land mapping applications.

3.1 Neural Network Development

The neural networks were developed using the Neuroshell 2 neural-network development program. This program implements several different neural-network algorithms, including back propagation, multilayer back propagation, and GRNN. The program does not require any programming by the user. To use the program, a set of inputs and outputs must be defined, and a suitable training set must be developed (William & Gucunski,1995).

The basic step to apply neural network is to define the problem or explicitly to define the input and the output. In the current case, the objective was to model the sea level and consequently, the available monthly mean sea level were considered as output. The inputs in the neural networks problem represent all the known variables that may affect the output i.e. MSL data in the current problem. The above sources of sea level variations were taken into consideration as inputs. The available meteorological data , the tides, and time were considered to be the input. It is advised here to choose the inputs as minimum as possible and to study the effect of removing the non- significant inputs.

The data in neural networks are categorized into three sets i.e. training or learning set , test set, and production set. The learning set is used to determine the adjusted weights and the biases of a network. The test set is used for calibration, which prevents overtraining networks. The test set should be approximately 10 to 40 percent the size of the training set of data (Neuroshell 2 tutorial, 1996) . The production set may be used to test the network's result with data the network has never seen before. In the current case, the MSL records (84 months) were divided into three sets. The first set with 60 records was used as training set, the second test with 6 records was used as test set, while the third set with 18 records was used as production set.

The Neuroshell 2 program offers several different types of learning concepts. Among them are the back-propagation networks which are known for their ability to generalize well on a wide variety of problems. Back-propagation networks are a supervised type of network, i.e. trained with both inputs and output. It is made up of interconnected nodes arranged in at least three layers. The input layer receives the input data patterns, and passes them into the network. The number of input nodes equals the number of input data values. The output layer produces the result. The hidden layers have no direct connection to input or output. Choosing the number of hidden nodes is usually done through experimentation. Too few hidden nodes will result in first or forward phase of back-propagation learning, an input pattern is applied to the network, and the resulting activity is allowed to spread through the network to the output layer. The desired results are then compared to the actual results produced by the network. This comparison results in an error for each node in the output layer. In the second, or backward phase, the error from the output layer is propagated back through the network to adjust the interconnection weights between layers (Caudill 1990). This process is repeated until the network's output is sufficiently accurate

On the other hand, the General Regression Neural Networks GRNN models, as learning model, can provide estimates of continuous variables, and converge to the underlying regression surface. Unlike back propagation, GRNN is a one-pass learning algorithm. This type of network can be used for any regression problem in which the assumption of linearity is not justified. Details of the algorithm are provided by Specht (1991).

For the current case, normal three-, four-, and five-layer back-propagation networks were tested. Three-, four-, and five-layer back-propagation models were also developed that had jump connections between layers. A GRNN model was also developed. Overtraining of neural networks is possible. The Neuroshell 2 program provides an automatic feature to save the network that minimizes the error of the test set.

3.2 Neural Network Results

The data sets were examined using all the available neural networks method offered by neuroshell2 the results of the best six models are illustrated only. The modelled MSL versus Measured MSL is presented for only two models. Fig. 3 indicates the results of GRNN model which shows close values between the modelled and measured MSL for the train and test sets and small deviation for the production set. The mean square error estimated for this model is minimum compared with the other model which indicates that this model is best to model and predict MSL. Fig. 4 shows the results of Jump Connection Net compared to measured MSL. The modelled and predicted MSL deviated from the measured values and the mean square error is the maximum value. The results of the Standard Net, Multiple Hidden Slabs (Ward net) 5 Layers, Multiple Hidden Slabs (Ward net) 4 Layers, and Recurrent Networks with Dampened Feedback methods show the same characterstics as GRNN method. The modelled and predicted MSL resulted from these models match with the measured MSL. The mean square errors are shown in Table 3. The GRNN metod is the more effective method in model and predict MSL.

4. CONCLUSIONS

The mean sea level along the coastlines is found to be variable from place to place and from time to time, according to the change in the weather conditions, temporal variations, and Sea Surface Topography SST influences. Accordingly, MSL can not be used in different applications without considering the main sources of its variations. The long period variation of MSL should be taken into consideration during the design, constructin , and maintanance of Coastal Structures. These long period variations may be modelled with sufficient records of sea levels taken at a certain tide gauge using e.g. Least squares method. In case of insufficient data records for sea levels the least squares does not give accurate results. In this paper , the Neural networks was introduced to model and predict the mean sea level compared to Least squares method.

The mathimatical model that reprsents the sea level variations was introduced. The availabe MSL data for seven years at Alexanderia associated with the avilable metrological data were used to model and predict mean sea level. The estimated mean square error from least squares results is 19 cm^2. The neural network methods were applied for the MSL at Alexanderia as output data while, the meterlogical data and tide effect were considered as inputs. The data were trained by different methods. The method of general regression neural networks gave mean square error 11.9 cm2. The other method of training show reasonable values better than least squares except Jump Connection Net. It is recommended to Use GRNN method to model and prict MSL.

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Appendices

Table 1 A Summary of the Main Characteristics of Monthly Mean Sea Level Data Used in This Study.

Site	Tide gauge location		Span of The time series	significant gabs	Chosen Spans
	φ	λ			
Alexandria	31º 13´	29º 55´	Jan. 1944 to Dec. 1989	Jan. 1948 to Dec. 1949	Jan. 1950 to Dec. 1989

Table 2 A Summary of the Main Characteristics of Atmospheric Pressure, Air Temperature, and Wind Data in the Present Study

site	span of the monthly time series
Alexandria	Jan. 1980 - Dec. 1986

Table 3 Mean Square Error MSE Estimated for Each Model

Model	MSE
Least Squares	19
General Regression Neural Networks	11.9
Jump Connection Net	21.9
Standard Net	16.5
Multiple Hidden Slabs (Ward net) 5 Layers	12.16
Multiple Hidden Slabs (Ward net) 4 Layers	12.1
Recurrent Networks with Dampened Feedback	14

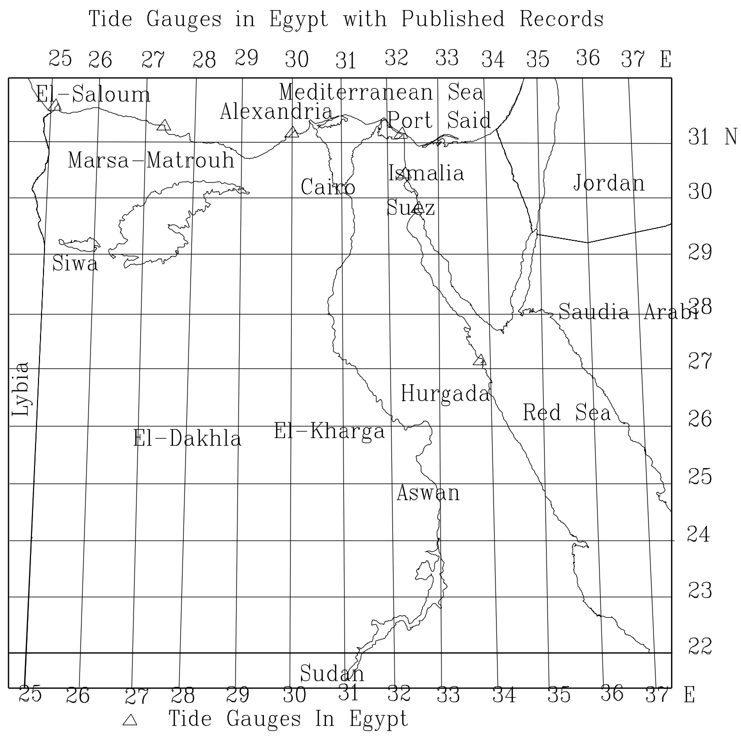

Fig. 1 Tide Gauges in Egypt with Published Records

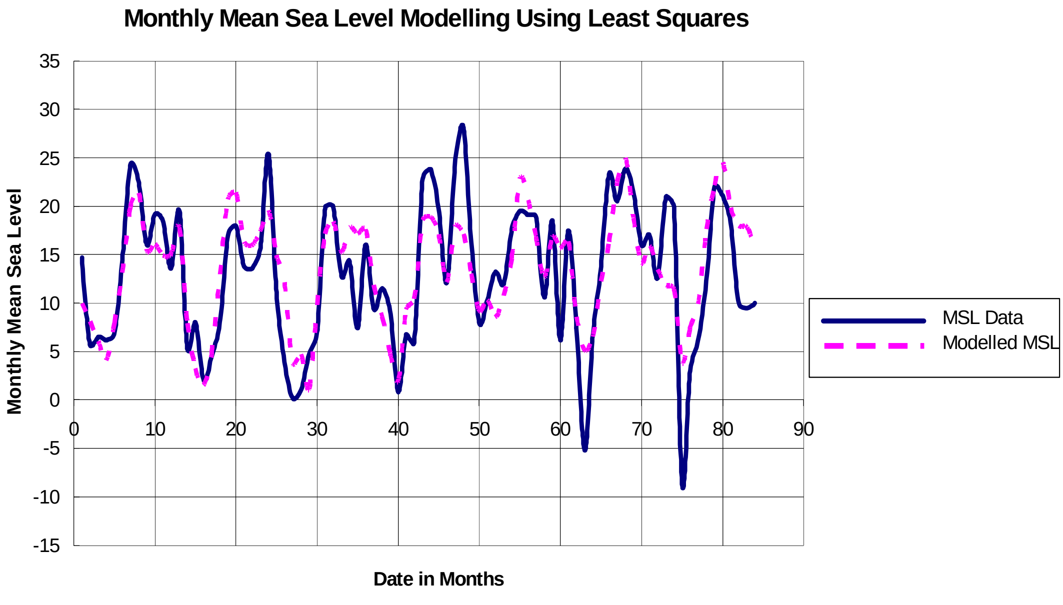

Fig. 2 Monthly Mean Sea Level Modelling Using Least Squares

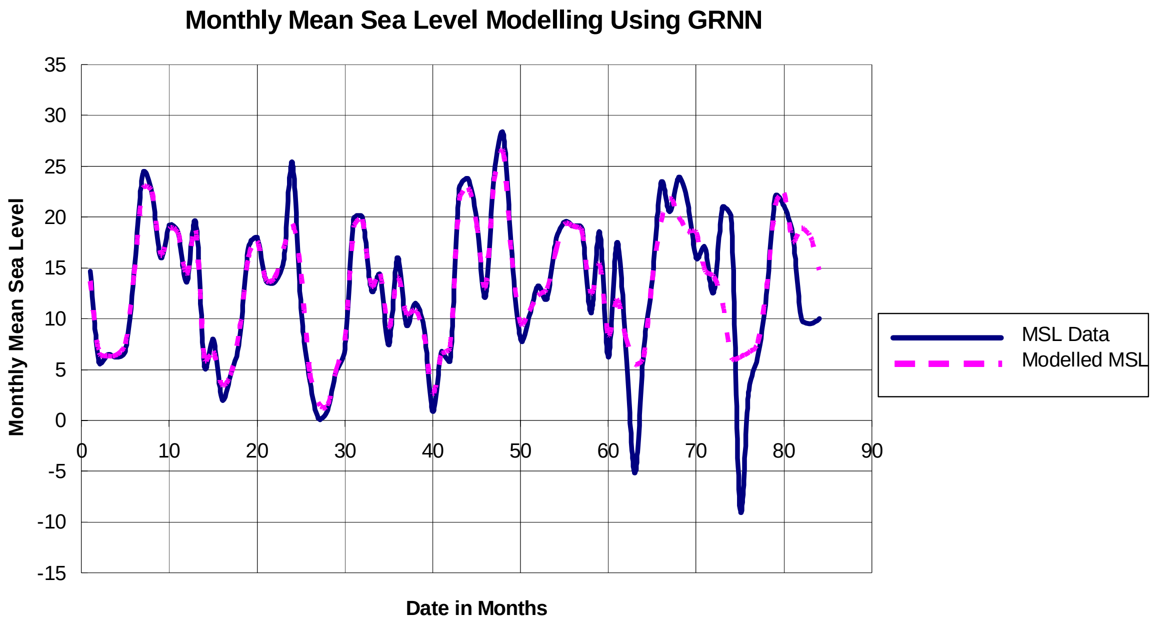

Fig. 3 Monthly Mean Sea Level Modelling Using General Regression Neural Networks

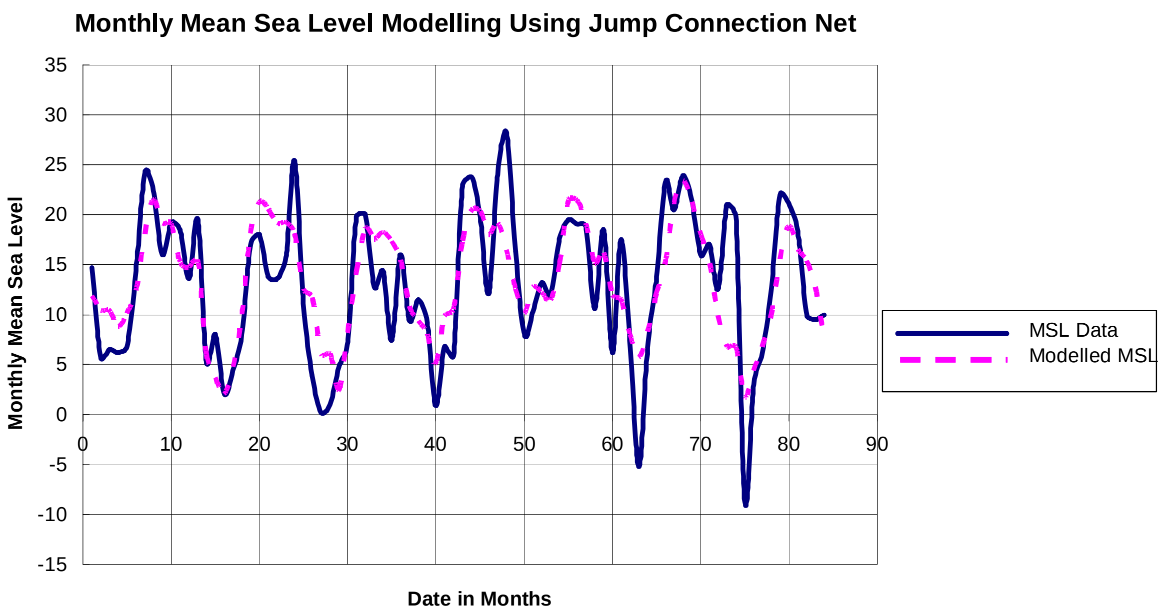

Fig. 4 Monthly Mean Sea Level Modelling Using Jump Connection Net