Hydrol. Earth Syst. Sci. Discuss., 4, 2497–2519, 2007
www.hydrol-earth-syst-sci-discuss.net/4/2497/2007/
© Author(s) 2007. This work is licensed
under a Creative Commons License.

Hydrology and Earth System Sciences Discussions

Papers published in *Hydrology and Earth System Sciences Discussions* are under open-access review for the journal *Hydrology and Earth System Sciences*

Prediction of littoral drift with artificial neural networks

A. K. Singh[1], M. C. Deo[1], and V. S. Kumar[2]

[1]Dept. of Civil Engineering, Indian Institute of Technology, Bombay, Mumbai, 400 076, India
[2]National Institute of Oceanography, Dona Paula, Goa 403 004, India

Received: 11 June 2007 – Accepted: 16 July 2007 – Published: 31 July 2007

Correspondence to: M. C. Deo (mcdeo@civil.iitb.ac.in)

Abstract

The amount of sand moving parallel to a coastline forms a prerequisite for many harbour design projects. Such information is currently obtained through various empirical formulae. Despite much research in the past an accurate and reliable estimation of the rate of sand drift has still remained as a problem. The current study addresses this issue through the use of artificial neural networks (ANN). Feed forward networks were developed to predict the sand drift from a variety of causative variables. The best network was selected after trying out many alternatives. In order to improve the accuracy further its outcome was used to develop another network. Such simple two-stage training yielded most satisfactory results. An equation combining the network and a non-linear regression is presented for quick field usage. An attempt was made to see how both ANN and statistical regression differ in processing the input information. The network was validated by confirming its consistency with the underlying physical process.

1 Introduction

Littoral drift indicates movement of sediments parallel to a coastline caused by the breaking action of waves. Ocean waves attacking the shoreline at an angle produce a current parallel to the coast. Such longshore current is responsible for the longshore movement of the sediment (Komar, 1976). Littoral drift poses severe problems in coastal and harbour operations since it results in siltation of deeper navigation channels so that ships cannot enter or leave the harbour area. An accurate estimation of the drift is needed in order to know the amount of excavation required so that corresponding budgetary provisions could be made in advance. Unfortunately this is easier said than done because the underlying physical process is too complex to model in the form of mathematical equations – either parametric or differential. Despite this, workable empirical formulae that relate the drift to a set of causative variables are currently in use. They are based on a collection of measurements made in the field or on a hydraulic model followed by a curve fitting exercise. The technique of fitting normally employed is non-linear statistical regression. However, it is well known that soft tools such as artificial neural networks (ANN) may provide a better alternative to the statistical methods (see e.g. ASCE Task Committee, 2000; Kambekar and Deo, 2003) and hence a variety of investigators have applied the technique of ANNs to solve problems in coastal engineering. These works typically include (a) wave height predictions (Deo and Naidu, 1999; Tsai et al., 2002; Makarynskyy, 2004; Altunkaynak and Ozger, 2004; Jain and Deo, 2004) (b) evaluating tidal levels and timings of high and low water (Deo and Chaudhari, 1998; Lee, 2004) (c) predicting sea levels (Vaziri, 1997; Cox, 2002) (d) forecasting wind speeds (Lee and Jeng, 2002; More and Deo, 2003) (e) establishing estuarine characteristics Grubert (1995) and (f) predicting coastal currents (Babovic et al., 2001) and (g) other met-ocean parameters (Krasnopolsky and Chalikov, 2002; Refaat, 2001). A comprehensive review of ANN applications in related areas can be found in Jain and Deo (2006). The application of ANNs, however, generally suffers from problems such as the lack of guarantee of success, arbitrary accuracy, and difficult choices related to training schemes, architectures, learning algorithms and control parameters. Any new application of ANNs that addresses these issues therefore deserves the attention of the potential user community. The current study is directed along this line and discusses an application of ANNs to determine littoral drift. Novel methods of network training are employed. An equation combining the ANN and the non-linear regression is presented for those desirous of making hand calculations. An attempt is made to see how both ANNs and statistical regression differ in processing the input information. The consistency of the network against the underlying physical process is then checked.

2 Network development

2.1 Training schemes

Most of the previous applications of ANNs to water flow has involved the use of feed-forward networks (ASCE Task Committee, 2000). The current study was also based on the same network architecture. Both a multi-layered perceptron network (MLP) as well as its variant, the radial basis function (RBF) was used. Training of the MLP was achieved with the help of alternative learning schemes such as Conjugate Gradient Polak-Rebiere Update (CGP), Powell Beale Restarts (CGB), Scaled Conjugate Gradient (SCG), the One Step Secant algorithm (OSS) and Resilient Backpropagation (RP). The reader is referred to Demuth et al. (1998) in order to understand details of these training algorithms.

2.2 The database used

The network was trained with the help of field observations. The location belonged to a four-km stretch of the coast off Karwar along the western coast of India. These field measurements have been collected by the National Institute of Oceanography at Goa over a period of four months starting 5 February 1990. The measurements of the significant wave height and average zero cross wave period along with the wave direction corresponding to the spectral peak were made with the help of a wave rider buoy. The breaking wave height and corresponding angle were derived as per the procedure in Skovgaard et al. (1975) and Weishar and Byrne (1978) and also visually confirmed. The width of the surf zone was measured daily using a graduated rope. The average longshore currents were measured daily (in terms of the distance covered in two minutes) using the Rhodanine-B type dye injected at the trap locations. The sediments were measured along a cross section of the surf zone at six stations at the same time and at a number of points vertically at each station. The suspended load was collected by mesh traps with circular openings and the bed load was gathered by streamer traps.

HESSD

4, 2497–2519, 2007

Prediction of littoral drift with artificial neural networks

A. K. Singh, M. C. Deo, and V. S. Kumar

EGU

The procedure of Kraus (1987) was used to determine the total sediment transport and this was based on the trapezoidal rule. A standard sieve analysis gave the median size distribution.

2.3 Network formulation

The phenomenon of littoral drift is influenced by a variety of causative factors - some of which could be of importance while others may be less influential in determining the rate of drift. The Shore Protection Manual (1984) as well as the Coastal Engineering Manual (2002) list these variables as incident significant wave height, H_s, breaking wave height H_b, significant or average zero cross period, T_z, angle of the wave at the time of breaking, α_b, width of the wave breaking (surf) zone, W, sediment size, d_{50}, and longshore current, V. A network with these parameters as input and the rate of drift, Q, as output, was considered. In total 81 input-output patterns were available through the measured data out of which 75 percent were randomly selected for training. Such a trained network was tested with the help of the remaining 25 percent of the patterns. It should be noted that the collection of these parameters simultaneously in fierce oceanic conditions is a difficult task due to the variety of instruments and equipment involved, and hence most of the time the investigators were only able to work with a limited sample size. An alternative to this is to resort to laboratory measurements. However, this is always associated with problems such as scale effects and ignorance of complex real sea conditions.

Out of all the causative variables listed above some are of primary importance while others are secondary. A sensitivity analysis of the inputs was done using the pruning method in which all causative variables were considered. The network was trained and the testing performance in terms of the various error measures described subsequently was noted. Thereafter each input was omitted one by one and the training and testing was repeated. This exercise revealed that exclusion of any of the parameters of H_s, T_z, H_b and α_b resulted in low performance. However, it was also noted that in addition to these, if we include W in preference to V and d_50 then the best performance is obtained. Table 1 shows the resulting performance over the testing pairs (when the best learning algorithm was employed) in terms of the multiple error criteria of the coefficient of correlation (r), root mean squared error (rmse) and mean absolute error (mae).

From Table 1 it is clear that a network that includes the width of the surf zone, W, in addition to that of H_s, T_z, H_b, and α_b gives the best accuracy for testing. However, it should be mentioned that this accuracy resulted after resorting to training by alternative schemes such as SCG, RP, OSS, CGP, CGB and not by adoption of any one of these randomly.

The number of hidden nodes in case of the above network (inputs: H_s, T_z, H_b, α_b, W) was 6. This was decided through trials conducted by increasing the number of hidden nodes one at a time, noting the performance of the trained network using the above listed error statistics, and stopping when such performance did not change with further addition of any the hidden nodes. A scatter plot checked the testing performance of this network (Fig. 1), which further qualitatively indicates a satisfactory result.

3 Regression models

In order to check how the neural network performs vis--vis the statistical regression, three new regression equations (linear multiple (LM) as well as non-linear (NL1 and NL2)) were fitted to the training data set. The resulting equations respectively are:

$$Q = -18.7152 - 13.379H_s - 0.3759T_z + 39.4895H_b + 0.3455\alpha_b + 0.2340W \quad (1)$$

$$Q = 0.28H_s^{-0.7693}T_z^{-0.0704}H_b^{2.7935}\alpha_b^{0.0005} \quad (2)$$

$$lnQ = -0.6566 - 1.2978H_s - 0.026T_z + 3.5802H_b + 0.0016\alpha_b + 0.0283W \quad (3)$$

The last 3 rows of Table 2 show the testing performance of these regression fits vis-à-vis the ANN, which confirms the necessity of employing ANNs for this problem in place of the traditional regression (higher "r" and lower "rmse" and "mae").

The selected network thus yielded a higher level of accuracy compared with the traditional regression models; the major underlying reasons were that ANNs represent a model-free estimation procedure as well as the flexibility in the mapping process involved.

3.1 Traditional formulae

The above study discussed how the network performed vis-à-vis the derived statistical regression models based on the data collected by the authors. Traditionally, however, most of the harbour and coast development works in India are carried out by using an empirical equation known as the Coastal Engineering Research Centre (CERC) formula and also by the Walton and Bruno equation. The CERC formula (Shore Protection Manual, 1984) assumes that the drift or Q is proportional to the longshore energy flux P_l, i.e.

$$Q = KP_l \tag{4}$$

where K is a dimensionless constant. The flux, P_l, in turn depends on the sediment characteristics (such as mass density, ρ_s and porosity, p), the breaking wave height H_b and its angle α_b with the shore and the wave period T. Specifically

$$P_l = \frac{1}{64\pi}[(\rho_s - \rho_w)g(1-p)]^{-1}\rho_w g^2 H_b^2 T \sin 2\alpha_b \tag{5}$$

In the above equation, ρ_w is the mass density of seawater and g is the acceleration due to gravity.

The Walton and Bruno formula on the other hand relies more on the derived parameters rather than the actual measured ones. The introduction of the surf zone width is also a specialty of this formula. Accordingly the longshore flux is given by:

$$P_{ls} = 0.008(\frac{V}{V_0}[(\rho_s - \rho_w)g(1-p)]^{-1}\rho_w H_b W V \tag{6}$$

The above equation is based on the assumption that the friction factor is 0.005 and that the theoretical non-dimensional longshore current velocity (v/v_0) is calculated with a mixing parameter of 40%. Equation (6) also uses the actual longshore current speed V.

The drift predicted by the above formulae was compared with its corresponding value actually measured in the field for the testing data conditions. Figure 2 shows the outcome. It clearly indicates that the field observations of the rate of sediment transport are entirely different than the corresponding values suggested by the two traditional formulae. The latter even indicated a wrong direction (i.e. negative values) of the littoral drift at times. The empirical constants used in these earlier derived equations were determined on the basis of measurements made at some alien locations where the coastal environment and the geomorphology as well as the topographic characteristics are very different from those found at the Indian site.

The unacceptable predictions obtained in the above exercise further confirm the necessity of using the ANN or ANN-regression hybrid models (described later) developed in this study.

4 Extended two-stage network

In order to increase the accuracy of the network prediction further, the network output (created with the following architecture: 5-6-1) was used as the input to another network. This additional network had one input node, one output node and two hidden nodes, selected from the trials mentioned earlier and shown in Fig. 3. Such a two-stage network, where a cause-effect network carries out the basic function approximation in the beginning and the recycler network later does the fine-tuning, was trained with the help of the training pairs and tested with the help of the testing pairs, as earlier. The testing results (Fig. 4) indicated that such a two-stage network performs much better than the earlier single-stage one, with "r" as high as 0.913 and rmse and mae as low as 3.006 (kg/sec) and 2.222 (kg/sec), respectively.

The use of two networks in this way seems to work better than that of an equivalent single network with three or so hidden layers since, in the case of the two-stage network, a pool of hidden neurons are allowed to learn independently and further by capturing the finer details left out after the basic learning process of the main network.

5 ANN-regression hybrid model

In the light of the fact that the NL1 regression was next in line in terms of the testing performance (Table 2) and that for quick field applications or for making hand calculations an equation would be preferred by the practitioners rather than the complex matrix of trained weight and bias, a new and simple network with one-input node belonging to the littoral drift rate, Q, given by Eq. (2), or NL1 model, and one output node belonging to the output value of Q was trained and further tested on the basis of the testing data set. The result was encouraging (r=0.832, rmse=4.349 (kg/sec), mae=3.411) although not as satisfactory as the two-stage ANN, and this is given in an equation form below:

$$\begin{aligned} Q = f(&-0.0555 f(-16.8Q_{NL1} + 16.8) \\ &+ 0.5738 f(16.8Q_{NL1} - 8.4) \\ &+ 0.312 f(16.8Q_{NL1} - 0.9999) \end{aligned} \quad (7)$$

where Q_{NL1} is the output from Eq. (2), and in general for any x,

$$f(x) = [1 + \exp(-x)]^{-1} \quad (8)$$

6 Consistency in following the physical process

The ANN developed by training cannot be put into practice unless its performance after training is found to be consistent with the underlying physical process. This may be viewed as especially necessary when one works with a rather limited sample size. A parametric study was therefore performed in which one input variable was varied over its full range keeping all other input quantities as constant. The idea was that the variation drawn in this way must match with the one that can be expected from the known physics of the underlying process. Thus an increase in the magnitude of the wave height should yield larger drift owing to an increase in the resulting longshore current. This can be clearly seen in Fig. 5a and Fig. 6a which indicate what happens to the trained network when significant wave heights and breaking wave heights become higher. Many studies in the past (e.g., Narasimhan and Deo, 1979) have shown that there is only a weak correlation between the wave height Hs and the wave period Tz. A given wave height can occur in association with any value of the wave period and thus can be associated with a range of values of the wave period. However, as Hs starts increasing from a low value, Tz also increases, but this trend continues only up to a certain higher value of Hs after which a reverse trend is observed. Thus very high Hs values usually correspond to some middle range of Tz values. Higher Hs would mean larger drifts and thus it can be guessed that the maximum drift would correspond to some middle range of Tz values. This relationship is confirmed in Fig. 7. Similarly higher values of the breaking angle, α_b, should mean a lower longshore current component and hence a smaller drift. A clear tendency towards this is not seen in Fig. 8 (although a weak trend may be speculated). This may probably be due to the limited range of α_b values involved during the period of data collection. The developed network can thus be seen to be generally consistent with the physical process of coastal sediment movement.

In order to understand why the ANN performed better than the regression, a parametric variation of Q against all causative variables was studied. Figure 5a and b as

HESSD

4, 2497–2519, 2007

EGU

well as Fig. 6a and b show examples of how the trained network and the regression Eq. (2) processed the input of increasing H_s and H_b values, respectively. The relatively low spread of points around the fitted line in the case of the regression (Fig. 5b and Fig. 6b) indicates that the regression performs rigid approximations with changing inputs compared with the ANN and therefore has resulted in a lower accuracy.

7 Conclusions

Feedforward networks were developed to predict the rate of littoral drift from a variety of causative variables. The use of a two-stage network system in which a regular network trained in the best possible manner first carries out a cause-effect modeling and another one later on fine tunes its outcome resulted in improved accuracy of predictions. New regression Eqs. (1) to (3) derived in this study can also be used to forecast the value of the littoral drift although with less accuracy then the ANN. An Eq. (7) combining the ANN and the non-linear regression is presented for quick field usage, although it may not predict the drift with accuracy equal to that of the ANN. An analysis showing how both ANNs and statistical regression process the input is also presented. It is found that the regression performs rigid approximations with changing inputs compared with the ANN and as a result, its accuracy drops. The developed network was found to be consistent with the underlying physical process and generally followed expected trends in the variation of the drift with an increase in the values of causative parameters.

References

Altunkaynak, A. and Ozger, M.: Temporal significant wave height estimation from wind speed by perceptron Kalman filtering, Ocean Engineering, 31(10), 1245–1255, 2004. 2499

ASCE Task Committee: The ASCE task committee on application of artificial neural networks in hydrology, J. Hydrol. Engg., American Society of Civil Engineers, 5(2), 115–136, 2000. 2499, 2500

Babovic, V., Kanizares, R., Jenson, H. R., and Klinting, A.: Neural networks as routine for error updating of numerical models, J. Hydraulic Eng., ASCE, 127(3), 181–193, 2001. 2499

Cox, D. T., Tissot, P., and Michaud, P.: Water level observations and short-term predictions including meteorological events for entrance of Galveston Bay, Texas, ASCE Journal of Waterways, Port, Coatsal and Ocean Engineering Division, 128(1), 21–29, 2002. 2499

Demuth, H., Beale, M., and Hagen, M.: Neural networks toolbox: users guide. The MathWorks Inc., Natic, MA, USA, 1998. 2500

Deo, M. C. and Chaudhari, G.: Tide prediction using neural networks, Journal of Computer-Aided Civil and Infrastructural Engineering, Blackwell Publishers, Oxford, UK, 13(1998), 113–120, 1998. 2499

Deo, M. C. and Naidu, C. S.: Real time wave forecasting using neural networks, Ocean Engineering, Elsevier, Oxford, U.K., 26(3), 191–203, 1999. 2499

Department of the Army, Corps of Engineers: Coastal Engineering Manual, US Army Coastal Engineering Research Center, US Govt., Washington-DC, USA, 2002.

Department of the Army, Corps of Engineers: Shore Protection Manual, US Army Coastal Engineering Research Center, US Govt., Washington-DC, USA, 1984.

Grubert, J. P.: Prediction of estuarine instabilities with artificial neural networks, ASCE Journal of Computing in Civil Engineering, 9(4), 226–274, 1995. 2499

Jain, P. and Deo, M. C.: Neural networks in ocean engineering, International Journal of Ships and Offshore Structures, Woodhead Publishers, 1(1), 25–35, 2006. 2499

Kambekar, A. R. and Deo, M. C.: Estimation of pile scour using neural networks. Appl. Ocean Res., 25(4), 225–234, 2003. 2499

Komar, P. D.: Beach processes and sedimentation, Englewood Cliffs, Prentice Hall, 1976. 2498

Kraus, N. C.: Application of portable traps for obtaining point measurements of sediment transport rates in the surf zone, J. Coastal Res., 3(2), 139–152, 1987. 2501

Krasnopolsky, V. M., Chalikov, D. V., and Tolman, H. L.: A neural network technique to improve computational efficiency of numerical oceanic models, Ocean Eng., 4(3–4), 363–383, 2002. 2499

Lee, T. L.: Back-propagation neural network for long-term tidal predictions, Ocean Eng., 31(2), 225–238, 2004. 2499

Lee, T. L. and Jeng, D. S.: Application of artificial neural networks in tide forecasting, Ocean

Eng., 29(1), 1003–1022, 2002. 2499
Makarynskyy, O.: Improving wave predictions with artificial neural networks, Ocean Engineering, 31, 709–724, 2004. 2499
More, A. and Deo, M. C.: Forecasting wind with neural networks, Marine Structures, Elsevier, Oxford, UK, 16(1), 35–49, 2003. 2499
Narasimhan, S. and Deo, M. C.: Spectral analysis of ocean waves: a study, Proceedings of Civil Engineering in Oceans IV conference, San Fransisco, ASCE, Vol II, 877–892, 1979.
Refaat, H. A. A.: Utilizing artificial neural networks for predictiong shoreline changes behind offshore breakwaters, J. Eng. Appl. Sci., 48(2), 263–279, 2001. 2499
Skovgaard, O., Jonsson, I. G., Bertelsen, J. A.: Computation of wave heights due to refraction and diffraction. Journal of Waterways, Harbor and Coastal Engineering, ASCE, 101 (1), 15–32, 1975. 2500
Tolman, H. L., Krasnopolsky, V. M., and Chalikov, D. V.: Neural network approximations for nonlinear interactions in wind wave spectra: direct mapping for wind seas in deep water, Ocean Modelling, available on-line, doi:10.1016/j.ocemod.2003.12.008, 2004. 2499
Tsai, C., Lin, C. and Shen, J.: Neural network for wave forecasting among multi-stations, Ocean Eng., 29(13), 1683–1695, 2002. 2499
Vaziri, M.: Predicting Caspian Sea Surface Water Level by ANN and ARIMA models, ASCE Journal of Waterways, Port, Coastal and Ocean Engineering Division, 123(4), 158–162, 1997. 2499
Weishar, L. L. and Byrne, R. J.: Field study of breaking wave characteristics. Proceedings of 16th Coastal Engineering Conference, American Society of Civil Engineers, New York, 487–506, 1978. 2500

Table 1. Effect of changing the inputs on the testing data set.

Input	Training algorithm	r	rmse (kg/sec)	mae (kg/sec)
H_s, T_z, H_b, α_b, W	CGB	0.867	3.664	2.929
H_s, T_z, H_b, α_b, V	RP	0.793	4.443	3.510
H_s, T_z, H_b, α_b, d_50	RP	0.831	5.137	4.390

Table 2. Comparison of the ANN and regression results on the testing data set.

Scheme	r	rmse (kg/sec)	mae (kg/sec)
ANN	0.867	3.664	2.929
LM	0.699	5.356	4.773
NL1	0.799	5.271	3.935
NL2	0.764	5.615	4.019

HESSD

4, 2497–2519, 2007

Prediction of littoral drift with artificial neural networks

A. K. Singh, M. C. Deo, and V. S. Kumar

EGU

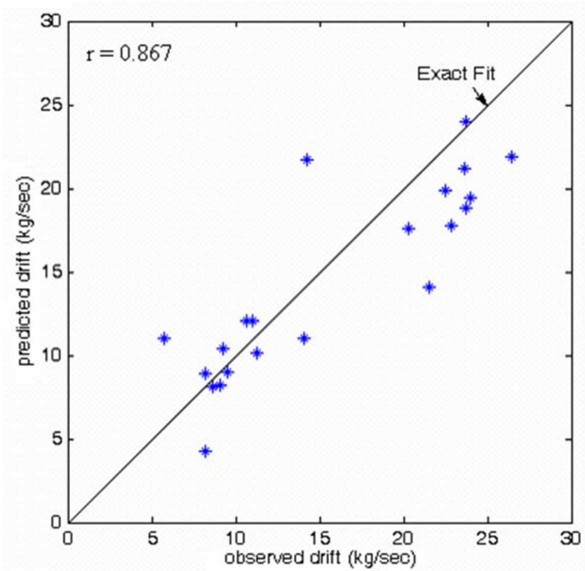

Fig. 1. Predicted versus observed drift (traditional ANN).

HESSD
4, 2497–2519, 2007

Prediction of littoral drift with artificial neural networks

A. K. Singh, M. C. Deo, and V. S. Kumar

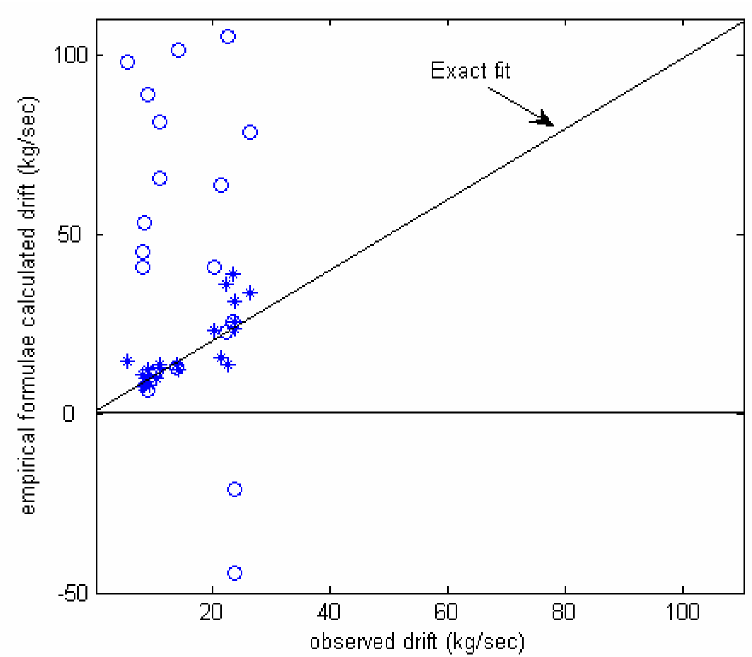

Fig. 2. Comparison of empirical formulae with observed drift.

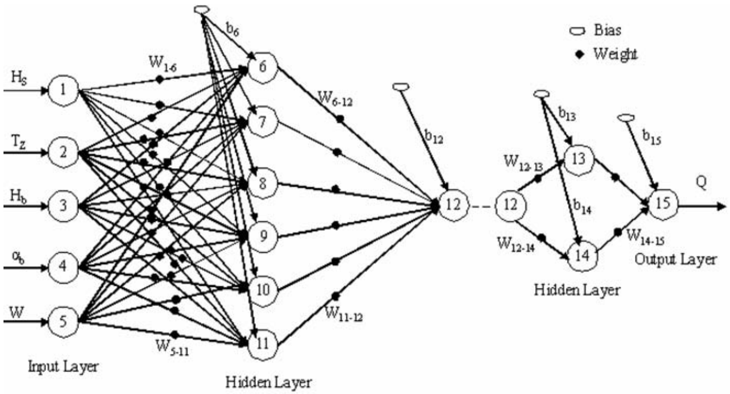

Fig. 3. The two-stage network.

HESSD

4, 2497–2519, 2007

Prediction of littoral drift with artificial neural networks

A. K. Singh, M. C. Deo, and V. S. Kumar

EGU

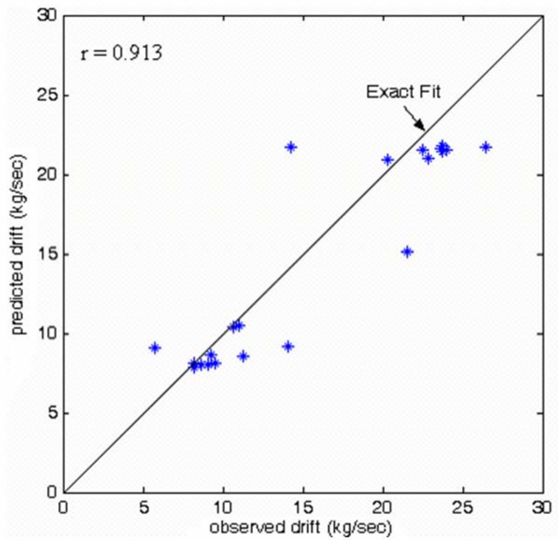

Fig. 4. Predicted v/s observed drift (revised ANN).

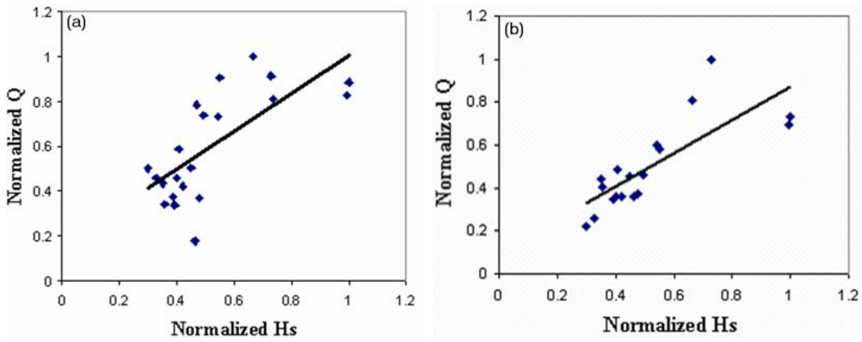

Fig. 5. (a) Input (Hs) processing by the ANN **(b)** Input (Hs) processing by regression.

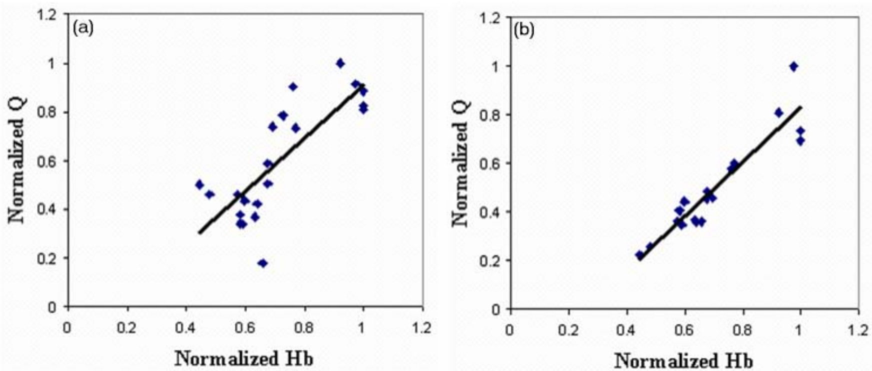

Fig. 6. **(a)** Input (H_b) processing by the ANN **(b)** Input (H_b) processing by regression.

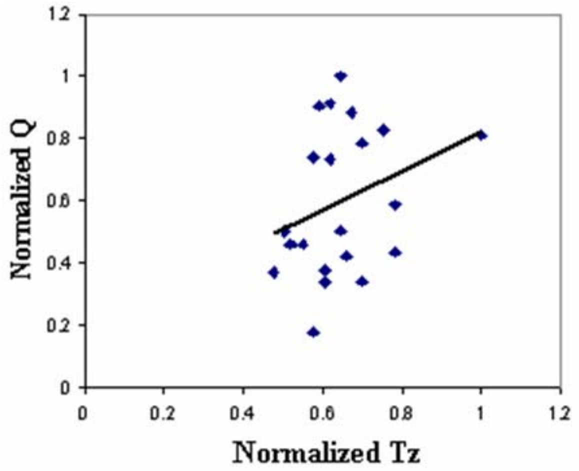

Fig. 7. Variation of the drift with wave period in the ANN.

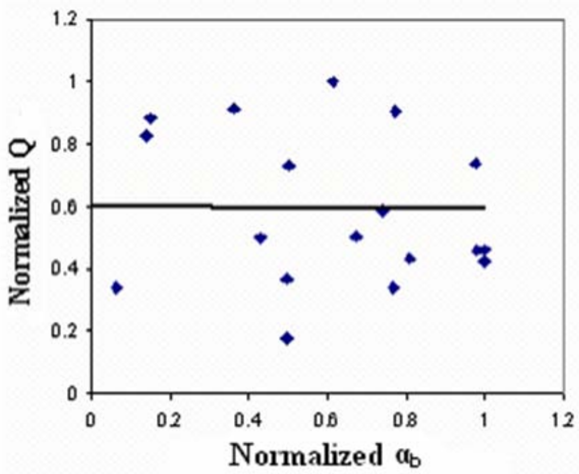

Fig. 8. Variation of the drift with the breaking angle in the ANN.