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Suspended Sediment Estimation for Rivers using Artificial Neural Networks and Sediment Rating Curves

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Abstract

The methods available for sediment concentration and flux estimation are largely empirical, with sediment rating curves being the most widely applied. In this study, a comparison is made between artificial neural networks (ANNs) and sediment rating curves for two rivers with very similar catchment areas and characteristics in the north of England. Data from one river are used to estimate sediment concentrations and flux in the other for both estimation techniques. A more traditional, split-sample approach is also used, in which part of the available data from a site is used to develop a predictive relationship, which is then tested with the remaining data from the same site. The results of the two estimation techniques and the two approaches for the derivation of predictive capability are compared and discussed. The potential advantages of ANNs in sediment concentration and flux estimation are highlighted. In particular, an ANN approach can give information about the structure of events (e.g., hysteresis in the sediment concentration - water discharge relationship, and the effect of antecedent conditions) which is impossible to achieve with sediment rating curves.

Key Words: Sediment rating curve, Artificial neural networks

Introduction

Sediment yield is defined as the total sediment outflow from a watershed measurable at a point of reference during a specified period of time. The sediment outflow from the watershed is induced by processes of detachment, transportation, and deposition of soil materials by rainfall and runoff. Estimates of sediment yield are required in a wide spectrum of problems such as the design of reservoirs and dams; transport of sediment and pollutants in rivers, lakes and estuaries design of stable channels, dams and debris basins; undertaking cleanup following floods protection of fish and wildlife habitats; determination of the effects of watershed management; and environmental impact assessment. Fine sediment has long been identified as an important vector for the transport of nutrients and contaminants such as heavy metals and micro-organics. Suspended sediment is important in its own right, since its presence or absence exerts an important control on geomorphological and biological processes in rivers and estuaries.

Sediment yield Y(t) at a given point in space (say, watershed outlet) can be represented as

$$Y(t) = \bar{Y}(t) \ + \ \varepsilon(t) \tag{1}$$

in which $\bar{Y}(t)$ is the mean value or deterministic component of Y(t), and ε(t) is the error from or fluctuation around the mean value or stochastic component of Y(t). The relative contribution $\bar{Y}(t)$ or ε(t) to Y(t) depends on the watershed and space–time scales. Clearly, Y(t) encompasses the full range of variability from being entirely deterministic to being entirely stochastic. All sediment models are special cases of (1).

Deterministic models can be distinguished as empirical and conceptual. Most of the empirical models are related to the Universal Soil Loss Equation (USLE) and its latter modifications. These models usually require long data records, so that average annual sediment yield can be determined. The conceptual models combine the mechanics of sediment transport with empirical relationships. Both the empirical and conceptual models approximate the physical processes controlling sediment yield.

Another way to represent the complex sediment behaviour is to interpret a sequence of sediment yield measurements as random. If the processes governing sediment yield such as soil particle detachment, entrainment, transport, and deposition are assumed to be stochastic and thus governed by the laws of probability, the sediment yield can be described by a stochastic process and associated probability distributions (pdf).

Some sediment yield models contain both deterministic and stochastic elements. A classic example is the relationship between sediment yield and runoff, represented by a line in the logarithmic plot. This is the deterministic part, $\bar{Y}(t)$, of the model. When the measurements are plotted, they encircle this line and most often will not lie directly on it. Thus the line represents only the mean trend of the sediment yield-runoff relationship, and fluctuations ε(t) above and below may be considered stochastic. A successful model will have to include a deterministic component or fluctuations around it.

Stochastic models of sediment yield can be grouped as regression models, time series models, entropy models and probability models. The regression models relate Y(t) empirically to rainfall R(t) and runoff Q(t). The spatial variability of these models is not considered. Stochasticity is represented by variations around the mean trend. In time series models a watershed is considered a spatially lumped system. Deterministic relationships between R(t), Q(t) and Y(t) are represented by a transfer function and stochasticity is modelled as an autoregression process. In entropy models the pdf of Y(t) is obtained using constraints based on the observed values of Y(t) and/or Q(t). Spatial variability of the variables is not accounted for. Probability models consider sediment yield Y(t) as a stochastic process, and so may the rainfall R(x,y,z,t) and runoff Q(t). The behaviour of Y(t) is described by its pdf or its joint probability density function with other stochastic sequences.

The application of physics-based distributed process computer simulation offers one possible method of prediction to assess the outcome of different management actions and long term management strategies. But the application of these complex software programs is often problematic, due to the use of idealised sedimentation components, or the need for massive amounts of detailed spatial and temporal environmental data which is not available. Simpler approaches are therefore required in the form of 'conceptual' solutions or 'black-box' modelling techniques. Neurocomputing provides one possible answer to the problematic task of sediment transfer prediction.

Many of the available techniques for time series analysis assume linear relationships among variables. In the real world, however temporal variations in data do not exhibit simple regularities and are difficult to analyse and predict accurately. Linear recurrence and their combinations for describing the behaviour of such data are often found to be inadequate. It seems necessary that nonlinear models such as artificial neural networks (ANNs), which are suited to complex nonlinear models, be used for the analysis of real world temporal data. ANN is a model inspired from the structure of the brain, and is well suited to such tasks as pattern recognition, combinatorial optimisation, and discrimination. The ANN learns to solve a problem by developing a memory capable of associating a large number of input patterns with a resulting set of outputs or effects. The ANN develops a solution system by training on examples given to it. These tools contain no preconceived ideas about the manner in which a model ought to be structured or work. It also provides a flexible approach, with the power to provide different levels of generalisation, and can produce a reasonable solution from small data sets. The modeller has control over the data inputs and irrelevant variables can be identified or removed during the model building process.

There are numerous studies related to the application of ANN's to various problems frequently encountered in water resources. The nonlinear ANN approach was shown to provide a good representation of the rainfall-runoff relationship (Hsu et al., 1995; Minns and Hall, 1996). The radial basis function type of ANNs was used to model the rainfall runoff process (Fernando and Jayawardena, 1998, Mason et al., 1996). Tokar and Johnson (1999) employed neural network methodology to forecast daily runoff as a function of daily precipitation, temperature, and snowmelt for the Little Patuxent River in

Maryland. Campolo et al. (1999a,b) used ANNs to forecast river flows during heavy rainfall and low-flow periods. ANNs were also considered a powerful tool in various groundwater problems (Ranjithan et al., 1993; Rogers and Dowla, 1994). Raman and Sunilkumar (1995) investigated the use of ANNs in synthetic reservoir inflow series generation. Boogaard et al. (1998) introduced Auto-Regressive neural networks (ARNN) for the nonlinear analysis and modelling of time series, whereas See and Openshaw (1998) outlined a methodology incorporating the neural network and fuzzy logic in forecasting problems. ANNs were also used in unit hydrograph derivation (Lange, 1998), regional flood frequency analysis (Hall and Minns, 1998), estimation of sanitary flows (Djebbar and Alila, 1998) and modelling hydraulic characteristics of severe contraction (Kheireldin, 1998). Abrahart (1998) presented an embedded solution for neural networks and the problem of accumulated error. There is no application example of ANNs to the estimation or forecasting of sediment concentration data in the literature. Since the installation of sediment concentration measurement instruments are costly, the results of this study are of significance.

The term forecasting is used in the study as in the case of having the same variable in both input and output layers. If the input layer contains variable(s) different from those of the output laye then the term estimation is preferred.

The Structure of the ANNs

The learning process, or training, forms the interconnection between neurons and is accomplished by known inputs and outputs, and presenting these to the ANN in some ordered manner. The strength of these interconnections is adjusted using an error convergence technique so that a desired output will be produced for a known input pattern.

Many training procedures are discussed in the literature. Error back propagation is one of the most commonly used procedures. The processing units are arranged in layers. The method is generally an iterative nonlinear optimization approach using a gradient descent search method. Mason et al. (1996) and Fernando et al. (1998) have used radial basis function networks for training. They concluded that ANNs trained either using radial basis function or error back propagation provided comparable estimations.

Error back propagation provides a feed forward neural network, giving the capacity to capture and represent relationships between patterns in a given data sample.

A neural network has an input layer, a hidden layer and an output layer. Each layer is made up of several nodes, and layers are interconnected by sets of correlation weights.

The pattern of connectivity and the number of processing units in each layer may vary within some constraints. No communication is permitted between the processing units within a layer, but the processing units in each layer may send their output to the processing units in the succeeding layers. The nodes receive input either from the initial inputs or from the interconnections.

Error back propagation involves two phases: a feed forward phase in which the external input information at the input nodes is propagated forward to compute the output information signal at the output unit, and a backward phase in which modifications to the connection strengths are made based on the differences between the computed and observed information signals at the output units.

At the beginning of a training process, the connection strengths are assigned random values. The learning algorithm modifies the strength in each iteration until the successful completion of the training. When the iterative process has converged, the collection of connection strengths captures and stores the knowledge and the information present in the examples used in the training process. Such a trained neural network is ready to be used.

When presented with a new input pattern, a feed forward network computation results in an output pattern which is the result of the generalisation and synthesis of what ANN has learned and stored in its connection strengths.

The neural network employed in this study possessed a three-layer learning network consisting of an input layer, a hidden layer and an output layer. Error back propagation is used as training procedure throughout the study. The equations related to this training procedure are available in all standard ANN text books.

Analysis of Data

In this study, flow and sediment concentration data of two stations are used. The first one is the Low Moor station on the River Tees. The River Tees is one of the principal rivers of north-east England. It rises in the North Pennines at Tees Head, at an altitude of 893 masl, and flows into the North Sea some

85 km to the east, at Teesmouth. The total catchment area is approximately 2400 km^2; the catchment area above the Low Moor Gauging Station is 1264 km^2. Broadly speaking, the catchment upstream of Low Moor may be divided into a steep upland headwater area underlain by Carboniferous geology in the west, and a lowland area underlain by Permian and Triassic geology in the east. A strong west-east precipitation gradient follows the topographic gradient: while the headwaters receive up to 2000 mm of precipitation annually, this drops to around 600 mm near the coast at Middlesbrough. As a consequence, the landscape of the upper Tees is characterised by peaty soils, moorland and rough grazing, while land use in the lower Tees is dominated by improved pasture and arable farming.

Extensive upland headwaters with high rainfall, low storage capacity and high drainage density give rise to an extremely flashy river regime. Snowmelt can also be an important component of runoff during the winter and spring. The Tees data considered in this study cover the period from 21-01-2000 to 30-03-2000 (Table 1).

The second station with sediment data is the Thornton Manor station on the Swale River in the Humber catchment. Since no was flow data observed at this station the flow data of Crakehill station on the Swale River is considered. The data was obtained during the LOIS study. An extensive sediment monitoring network was established within the LOIS programme, involving the main tributaries of the River Humber (UK). One of the key objectives of the Land-Ocean Interaction Study (LOIS) established in 1992, was to quantify and characterise the flux of materials from river basins to oceans (Wass and Leeks, 1999). This provided an opportunity to deploy an extensive suspended sediment river network within the rivers of the study area, on a scale not previously attempted in the UK. A turbidity monitoring system was developed to provide a continuous record of suspended sediment concentration in the rivers, from which the fluxes were calculated. Linear relationships were established between suspended sediment concentration and turbidity to enable the conversion of nephelometric turbidity (NTU) to suspended sediment concentration (mg/l). The measurements were undertaken during the period October 1994-November 1997.

The Humber drains over one-fifth of the area of England, an area that is characterised by a wide range of geology, climate, soils and land use. In general, the north-western part of the catchment is dominated by Carboniferous millstone grits and limestones forming the upland headwaters. Towards the south and east, the land is relatively low lying with the Permo-Triassic sandstone and Cretaceous chalk aquifers comprising the solid geology, which is often overlain by superficial glacial and alluvial deposits (Wass and Leeks, 1999). Annual precipitation ranges from 600 mm in the east to over 1600 mm on the Pennine Hills, the majority of which falls as frontal rain associated with the prevailing westerly airstreams. In the Humber catchment the largest suspended sediments come from the biggest catchments, with the River Trent contributing 33% , the River Ouse 31% , the River Aire 16% , the River Don 14% and the River Wharfe 6% . These rivers are in turn comprised of smaller subcatchments. The load of the main rural Ouse is dominated by sediment derived from River Swale (53%) and River Ure (38%) with the River Nidd contributing around one tenth of the load. The primary considerations when locating the sediment monitoring equipment were, firstly, that the network should mirror the manual sampling network as a whole; secondly, that fluxes should be monitored close to the tidal limit or at major catchment outlets and, thirdly, that there should be river flow monitoring stations nearby. An overview of the river monitoring strategy is given by Leeks et al. (1997). The related information for the available flow and suspended data is presented in Tables 1 and 2. The suspended data is unfortunately not continuous throughout the observation period in all five stations. The continuous observation period for Swale sediment and flow data considered in this study covers the period from 10-11-1994 to 25-12-1994 (Table 1).

The catchments providing sediment to the River Swale and the River Tees have similar characteristics justifying the utilisation of the data for both rivers during the training and testing stages of the ANNs. The data for both rivers correspond to different years but to the winter season.

The first order correlation coefficient for Swale Crakehill flow - Swale Thornton Manor sediment is 0.57 whereas it is 0.86 for Tees Low Moor flow-sediment.

Figures 1 and 2 illustrate the relation between suspended sediment and flow for River Swale and River Tees, respectively.

Table 1. River flow and suspended sediment data

	River	Station	Observation period
Flow (Time step: 15 min; unit: m^3/s)	Swale	Crakehill	from 01-09-93, 09:00 to 14-04-97, 03:00
	Tees	Low Moor	from 21-01-2000, 11:30 to 30-03-2000, 19:45
Sediment (Time step: 15 min; unit: m^3/s)	Swale	Thornton Manor	from 01-09-93, 09:00 to 14-04-97, 03:00
	Tees	Low Moor	from 21-01-2000, 11:30 to 30-03-2000, 19:45

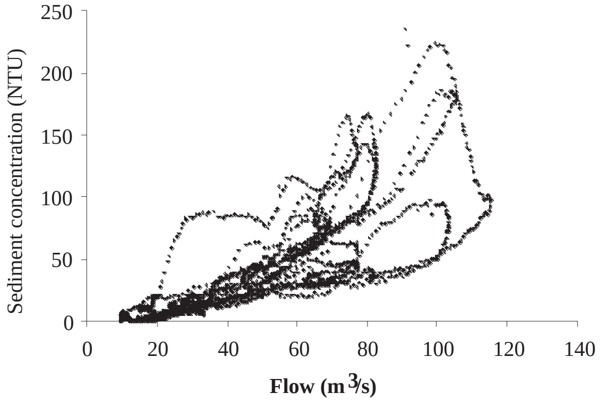

Figure 1. Plotting of River Swale Thornton Manor suspended sediment values versus River Swale Crakehill flow values for the period from 10-11-1994 to 25-12-1994.

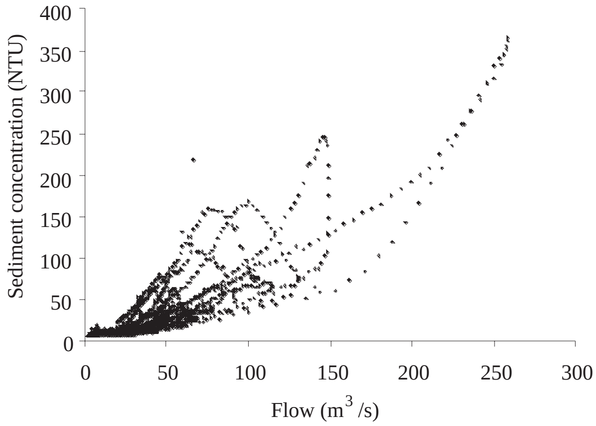

Figure 2. Plotting of River Tees Low Moor suspended sediment values versus the flow values for the period from 21-01-2000 to 30-03-2000.

Application of ANNs to the Data

A code in FORTRAN was written following the steps explained in part 2.

The application of the ANNs to estimate the suspended sediment concentration consisted of two steps. The premiere step was the training of the neural networks. The back propagation method was employed to train the ANNs. The determination of the number of hidden layers and the number of nodes both in the input layer and in each hidden layer which provided the best training results was the primary consideration in the training procedure. The criterion for the evaluation of the training simulation was the final MSE value computed as given by Raman and Sunilkumar (1995). Initially randomly generated normal values between –3 and 3 are assigned for correlation weights. The training input and output values are scaled simply using the equation:

$$c\frac{x_i - x_{\min}}{x_{\max} - x_{\min}} + d \qquad (2)$$

where x_{min} and x_{max} represent the minimum and maximum of all the values in the input or the output layer throughout all patterns. Different values can be assigned for the scaling factors c and d. If c and d are equal to 1 and 0, respectively, the scaling is linear. Since linear scaling prevents extrapolation, c and d can take values like 0.8 and 0.1 or 0.6 and 0.2, respectively. If the variable in each layer is different, e.g. if river flow is the input and the suspended sediment is the output, the scaling is realised for each layer separately. In the case of having the same variable in both input and output layers, i.e. in forecasting the suspended sediment using the previous sediment values as input, all the values in both layers are scaled together. In this study the scaling parameters c and d are taken as 0.6 and 0.2, respectively. Once the training stage was completed, the testing stage began using the optimum values found for the number of nodes in each layer, the number of hidden layers, the learning rate, the momentum rate and the correlation weights.

After finalising the training stage it is seen that one hidden layer was sufficient to capture the complexity of the problem and that an addition of a further layer(s) did not provide an improvement. The optimum node numbers are found as 6 for the input layer and 3 for the hidden layer, respectively, after trying the various combinations. The optimum learning, η, and the momentum, α, rates were found after trying various values and observing the MSE produced at the end of the testing stage. It is seen that picking high values like 0.5 and 0.9 for η and α as done by Raman and Sunilkumar (1995) throws the network into oscillations or saturates the neurones. Saturation occurs when the net input to a neurone is a large value (either positive or negative) and variations in the input thus have little effect on the output (Eberhart and Dobbins, 1990). It is seen that η and α should be decreased if the number of input and output patterns increased. The iteration number, on the other hand, increases decreasing η and α values. In this study 0.02 and 0.01 values are found adequate for η and α, respectively. The testing stage results using these parameter values are presented in detail in the following part of the paper.

The estimation and forecasting of suspended sediment using the previous observed data on the same station

In this part of the study, the efficiency of ANNs in estimating the future sediment data using the previous observed flow and sediment data during the training stage was investigated. For this purpose, 15 minutes flow and suspended data observed at the River Tees Low Moor station between 23^{rd} January and 26^{th} February 2000 are used for training ANNs. Initially the ANN's are used for forecasting the sediment concentration values at time t using the previous sediment values at times t-4, t-8, ...,t-24 as input. The time interval between input values was 1 hour and therefore the input layer covered a total period of 6 hours. The testing stage covered the following time period between 26^{th} February and 17^{th} March 2000. The mean square error (MSE) obtained at the end of the testing stage was 13.20. Increasing or decreasing the number of inputs did not provide an improvement in The MSE. For example, the MSE was equal to 16.60 and 17.20 for 8 inputs and 3 inputs, respectively. Similarly increasing the number of hidden layers from one to two or three did not decrease the MSEs. The performance of the ANNs are compared with those of the classical Autoregressive Models. The parameters of the AR(1) and AR(2) models are computed with the data used at the training stage of the ANNs and the forecasting is carried out for the testing period data. The obtained MSE were 22.10 and 20.18, respectively, being higher than the corresponding ANN results. The AR(1) and AR(2) models were also employed for the logged sediment values providing MSE values like 20.10 and 18.70, respectively.

The input layer consisted of six flow values at times t-4, t-8, . . . , t-24 and the output layer had the unique suspended sediment concentration at time t. The testing stage covered the following time period between 26^{th} of February and 17^{th} of March 2000. The ANN estimated time series were close to the observed one but the peaks were underestimated (Figure 3). Sediment rating curves were employed for the purpose of comparison with the corresponding ANN ones. The sediment rating equation between flow and sediment concentration values for the Low Moor station for the period between between 23^{rd} January and 26^{th} February 2000, i.e. the training period of the ANN process, was as follows:

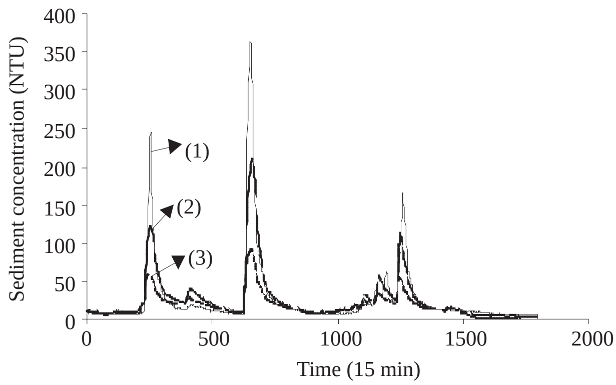

Figure 3. Comparison of observed sediment concentration values, (1), with the ones estimated by ANNs, (2), and sediment rating equation, (3), for Tees River Low Moor station for the period from 26-02-2000 to 17-03-2000.

$$SC = 1.13Q^{0.79} \tag{3}$$

where SC and Q represent the sediment concentration and flow values, respectively. This relation was used to estimate the sediment concentration values within the period from 26^{th} February to 17^{th} March 2000, i.e. the testing period of theANN process, and the results are presented in Figure 3 (Curve 3). It is clear that the ANN estimations are closer to the observed ones in comparison with the ones obtained using the sediment rating relation. The observed peaks are approximated by ANNs significantly better than with the the sediment rating relation. The total sediment amount estimated by ANNs and by sediment rating relation was 3710 tons and 2080 tons, respectively, being 12% and 50% lower than the observed 4202 tons.

The same study was repeated for the River Swale. River Swale Crakehill station flow values were used as input during both the training and testing stages of the ANNs to estimate the River Swale Thornton Manor station sediment concentration values. The training and testing stages included values within the period from 10^{th} November to 2^{nd} December 1994 and from 14^{th} December to 25^{th} December 1994, respectively. The ANN estimations are compared with the corresponding sediment rating ones obtained using

$$SC = 0.007Q^{2.03} \tag{4}$$

relation in Figure 4. Again here the ANN estimations are closer to the corresponding observed ones. The total estimated sediment amount for ANNs, 958t, and the sediment rating relation, 627t, was 20% and 48% less than the observed 1207t, respectively.

To be able to test whether the ANN approach can give information about the structure of events the hysteresis in the sediment concentration obtained by ANNs and sediment rating relation are compared with the corresponding observed one in Figures 5 and 6 for both stations. It is seen that the turn direction of the hysteresis estimated by ANNs is the same with the observed one in both cases.

The estimation of suspended sediment using the data in the nearby river

In this part of the study the ANNs are used to estimate the suspended sediment concentration values using the flow values as input. The 15 minutes flow and suspended sediment concentration values observed in the River Swale within the period from 10^{th} November 1994 to 25^{th} December 1994 were used for the training stage. The six flow values (t-4, t-8, ..., t-24) constituted the input layer to estimate the unique suspended sediment value at time t. The time interval between input values was 1 hour and therefore the input layer covered a total period of 6 hours. The testing of the trained ANNs was accomplished with the 15 minutes flow and suspended data of the River Tees Low Moor station for the period between 23^{rd} January and 7^{th} March 2000. Examining the results presented in Figure 7 the ANN estimated suspended sediment concentration time series generally approximates the observed one underestimating the peaks. The MSE and the ANN estimated sediment totals at the end of the testing period were 377 and 3946 tons, respectively. The difference between the estimated and observed sediment total (5664t) was 30% due to the underestimation of the peaks.

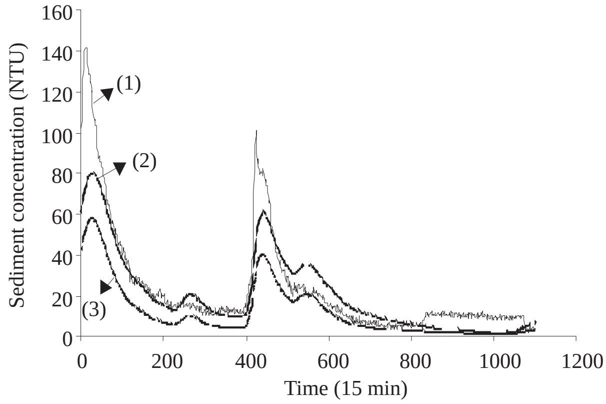

Figure 4. Comparison of observed sediment concentration values, (1), with the ones estimated by ANNs, (2), and sediment rating curve, (3), for River Swale Thornton Manor station for the period from 14-12-94 to 25-12-94.

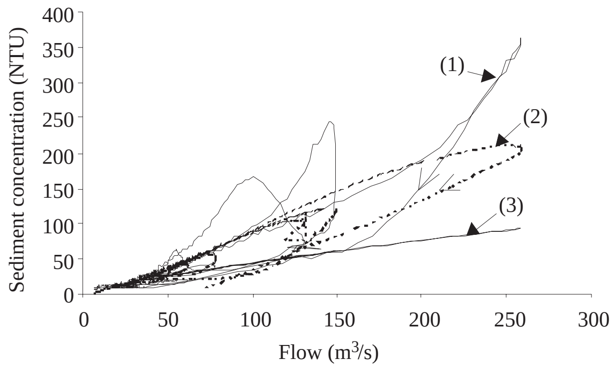

Figure 5. Comparison of the observed Hystheresis ,(1), with the ones estimated by ANNs, (2), and by sediment rating relation, (3), for Tees Low Moor station for the period between 26th of February and 17th of March 2000.

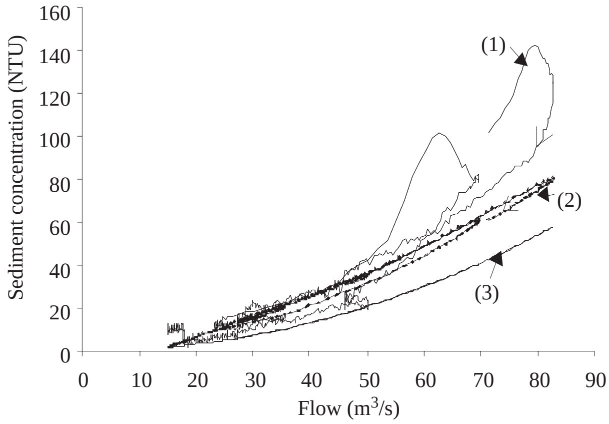

Figure 6. Comparison of the observed hysteresis, (1), with the ones estimated by ANNs, (2), and by sediment rating relation, (3), for Swale Thornton Manor station for the period between 14th December and 25th December 1994.

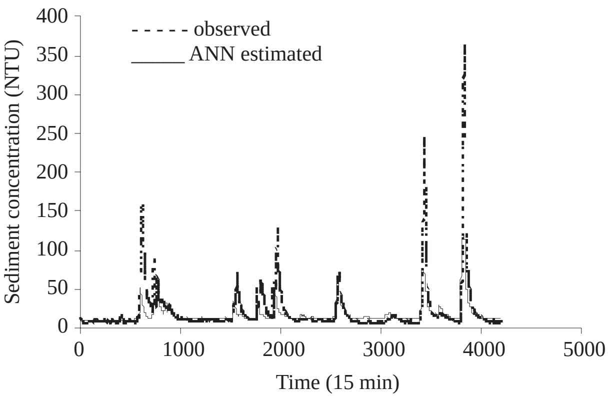

Figure 7. The estimated River Tees Low Moor suspended sediment values for period from 23-01-2000 to 07-03-2000 using the 6 (t-4,..,t-24) Low Moor flow values as input with an MSE=377. For the training of ANN's the sediment and flow data of River Swale Thornton Manor station was used.

The study is repeated afterwards, replacing the training data with the testing data and vice versa, i.e. the River Tees data was for training and the River Swale data for testing. The time periods of the data considered during both stages were the same as the previous one. The results presented in Figure 8 show that the ANN estimated series capture the general behaviour of the observed Swale series underestimating the peaks in general. However, the ANN estimated sediment total, 8233 tons, is just 3.3% higher than the observed 7970 tons with an MSE equal to 607. The small difference shows that the underestimation of peaks is compensated for by overestimation of low flows.

These results show that if river flow and suspended sediment data from a nearby river with similar catchment characteristics are available, the general behaviour of the suspended sediment time series can be estimated using the available flow series for the corresponding time interval. The data time periods for the Rivers Swale and Tees were different, though both being from winter. It should be considered that the results are obtained by training ANNs for a very limited period. It is clear that with the availability of longer continuous data the ANNs would be trained for more input and output patterns, increasing the accuracy during the testing stage.

It should be kept in mind that for the annual sediment budget computations for the related reservoirs the annual sediment totals are considered. Therefore the obtained results are of significance since the ANN estimated suspended sediment values represent the average behaviour, providing a total sum close to the original one.

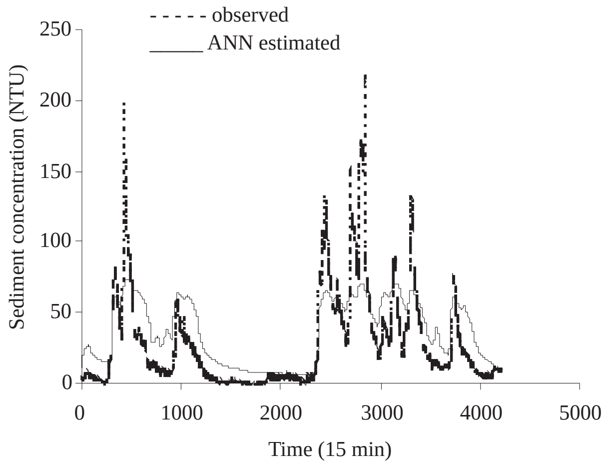

Figure 8. The estimated River Swale Thornton Manor suspended sediment values for period from 10-11-1994 to 25-12-1994 using 6 (t-4,..,t-24) Thornton Manor flow values as input with an MSE=607. For the training of ANNs the sediment and flow data of River Tees Low Moor station was used.

Conclusions

In the presented study ANNs are used for estimating suspended sediment concentrations. It is shown that even in the absence of observed sediment data from was possible to obtain reliable corresponding estimates by training ANNs using the sediment and flow data in a nearby river. The estimations obtained by ANN's were significantly superior to the corresponding classical sediment rating curve ones. It is seen that an ANN approach can provide information about the structure of events (e.g., hysteresis in the sediment concentration - water discharge relationship, and the effect of antecedent conditions) which is impossible to achieve with sediment rating curves.

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