Conjunction of a newly proposed emotional ANN (EANN) and wavelet transform for suspended sediment load modeling

Elnaz Sharghi, Vahid Nourani, Hessam Najafi and Huseyin Gokcekus

ABSTRACT

Suspended sediment load (SSL) time series have three principal inherent components (autoregressive trend, seasonality and stochastic terms) and the overall performance of an SSL modeling tool is associated with the correct estimation of these components. In this study, novel developments of artificial neural network (ANN) models, emotional ANN (EANN) and hybrid wavelet-EANN (WEANN), are employed to estimate the daily and monthly SSL of two rivers (Upper Rio Grande and Lighvanchai) with different hydro-geomorphological conditions. The overall results obtained via autoregressive models, the ANN and EANN, specify the supremacy of EANN (with a few hormonal parameters) against ANN due to the EANN better training the model versus extreme conditions. Also, the obtained results exhibit that the WEANN model could improve the SSL modeling up to 42% and 14% for daily modeling and up to 141% and 87% for monthly modeling in the Upper Rio Grande and Lighvanchai Rivers, respectively.

Key words | emotional artificial neural network, Lighvanchai, seasonality models, suspended sediment load, Upper Rio Grande, wavelet transform

INTRODUCTION

Suspended sediment load (SSL) is a fundamental subject in river management due to its being highly correlated to water quality, contaminant transport, silting and soil erosion and loss (i.e. reservoir sedimentation), which means strong recreational and ecological impacts (Frémion et al. 2016). Difficulties in the estimation of each component of the process make the estimation of the total amount of transported sediment notably difficult.

As a result, for SSL modeling, the black-box models can be more efficient than the physical base models due to the complexity of SSL time series (Salas et al. 1980). For instance, linear and stationary time series can be properly modeled by the classic black-box methods such as Seasonal Auto-Regressive Integrated Moving Average (SARIMA) (Hansen & Nelson 1997). But such models (e.g. SARIMA) may not be suitable for non-linear and non-stationary hydrological time series. As an alternative, non-linear artificial intelligence (AI) based methods, especially the artificial neural network (ANN), have achieved real success in the modeling of hydrological time series (Luo et al. 2016; Emamgholizadeh & Demneh 2018) due to their remarkable advantages, including (Kim & Valdés 2003):

- Being black-box tools, they can be easily used in the absence of prior knowledge about the physics of the phenomena.
- These have inherent non-linearity, provided through activation functions and neurons, so they can handle non-linearity of process.
- It is possible to have different input variables, thus they can consider time-space variability.
In spite of the performance of the neural network in hydrologic modeling, it may be difficult to deal with highly non-stationary and seasonal variations. To overcome this problem, the wavelet-based data preprocessing technique can be a good solution. The wavelet transform (WT) is an appropriate tool for extracting inherent (hidden) frequencies and obtaining valuable temporal information from large data sets. Hence, the hybrid wavelet-ANN (WANN) model has been able to show good performance and is widely applied for hydrological modeling, not only for sediment modeling but also many other hydrological variables and processes such as rainfall runoff, groundwater and river flows (Nourani et al. 2014). For example, Liu et al. (2015) developed the WANN model for daily SSL modeling of Kuye River (China). Due to the results of this study, the WANN model showed higher prediction accuracy than the sediment rating curve (SRC) model (up to 58%) or the ANN model (up to 27%). Also, Alizadeh et al. (2017) developed ensemble models by employing multiple WANN models for daily SSL modeling of Skagit River (USA) and achieved acceptable forecasts up to 3 days in advance. Himanshu et al. (2017) developed a support vector machine (SVM) with WT for prediction of daily SSL and showed that the wavelet-SVM model is superior to the conventional SVM model and could be used as an effective forecasting tool for hydrological applications.

From the biological perspective, an animal’s response for the same actions can be varied under various conditions because hormones may affect its neurophysiological reactions. As a result, lately the emotional ANN (EANN) model was proposed as a new development of the ANN model by linking artificial emotions into the traditional ANN framework (Khashman 2008; Lotfi & Akbarzadeh-T. 2016). As the first application in hydrology, Nourani (2017) investigated the ability of the EANN model in rainfall-runoff modeling (at daily and monthly time scales) and demonstrated that the EANN model could outperform the conventional ANN model. Generally, good performance in dealing with short observed data, and greater accuracy in prediction of peak values are some of the EANN advantages.

Obviously, like other data-driven models, in the presence of highly non-stationary and seasonal variations data preprocessing methods may be able to obtain better performance of modeling. In this way, as a novel strategy, EANN and the combined wavelet-EANN (WEANN) models have been investigated in this study for SSL modeling.

To the best of the authors’ knowledge, there is no published report investigating the ability of EANN and WEANN models in SSL modeling; thus, the purpose of this research is to investigate the ability of the different AI based models (i.e. ANN, WANN, WEANN and EANN) and traditional SARIMA (as a benchmark model) in SSL modeling. For this purpose, the daily and monthly data sets from two different rivers (in terms of geomorphological conditions) were used and the results obtained were compared.

MATERIALS AND METHODS

Study area and data set

In the current research, the data from two case studies, the Lighvanchai and Upper Rio Grande Rivers, were used to implement the proposed methodology. These rivers are located in northwest Iran in Azerbaijan province and the west of the USA, in Colorado and New Mexico states, respectively (see Figure 1).

The used SSL time series data are obtained from Iran Water & Power Resources Development Co. (IWPC) for Lighvanchai station and the United States Geological Survey’s website (USGS – https://cida.usgs.gov/sediment/) for the Rio Grande (at Otowi Bridge) station. The time series data for 28 years, from 1987 to 2015 for the Lighvanchai River and 39 years, from 1976 to 2015 for Upper Rio Grande River, were employed in the modeling process; these records were divided into two sub-sets: the first 75% and the remaining 25% were used for training and validation purposes, respectively. Table 1 shows the statistical characteristics of SSL data for both rivers at daily and monthly time scales. The table reveals that the volume and also the standard deviation of SSL in the Upper Rio Grande River are much greater than that of Lighvanchai, which means there are greater amounts of SSL and greater diversity for the Upper Rio Grande.

The Lighvanchai River is one of the major sub-tributaries of the Ajichai River, which discharges to Urmia Lake. The Lighvanchai watershed is located between 37° 43′ and
37\(^\circ\) 50\('\) North latitude and 46\(^\circ\) 22\('\) and 46\(^\circ\) 28\('\) East longitude on the northern slope of Sahand Mountain (northwestern Iran). The watershed area is approximately 142 km\(^2\) (Figure 1). Watershed altitude varies between 1,263 m and
3,679 m above sea level. The rainfall peaks in winter and spring. The watershed contains medium vegetative land cover, as a rural region. The topography is steep with an average slope of 11%. Consequently, the soils are disposed to erosion to some extent.

The Rio Grande (or Rio Bravo in Mexico) is an interstate and international river. It rises in Colorado and flows southward for more than 643 km across New Mexico, and then forms the boundary between Texas and Mexico for about 1,930 km to its mouth. The Upper Rio Grande River runs 1,100 km from its headwaters in Colorado through New Mexico and northern Mexico to Ft. Quitman, Texas. Along its river corridor, it is a primary source of irrigation water for food, fiber and feed production and is used as a source for municipal supply by the cities of Albuquerque, Las Cruces, El Paso and Ciudad Juarez. The Upper Rio Grande has a drainage area of about 10,000 km², less than a fifth of the water-producing area of the Rio Grande basin.

The Upper Rio Grande watershed has a greater Gravelius Coefficient than that of Lighvanchai. This characteristic may cause the Upper Rio Grande River to have more quick response for an identical event of precipitation compared to the Lighvanchai River, which results in greater rate of sediment transport in an identical soil type situation (see Table 1, the Mean row). In brief, by comparing the characteristics of the two watersheds, such as SSL, elevation, slope, area, etc., it can be inferred that the Upper Rio Grande watershed can be considered as a wild watershed compared with the Lighvanchai watershed in generating sediment. This means that the Upper Rio Grande watershed experiences a more irregular and non-linear pattern in its hydro-environmental processes (especially in SSL) rather than well-dominated seasonal weather.

### Methods used and efficiency criteria

In this study, the different AI-based models (i.e. ANN, WANN, WEANN and EANN) and SARIMA were employed for SSL modeling. Furthermore, Root Mean Square Error (RMSE), Nash-Sutcliffe (E) and Nash-Sutcliffe for peak values (Epeak) were used as evaluating criteria. Brief descriptions of the mathematical concept for EANN, WEANN and WANN models and evaluation criteria are
provided in Appendix A (available with the online version of this paper).

RESULTS AND DISCUSSION

As the benchmark model, the SARIMA model was examined for the SSL modeling of the rivers. SARIMA models can be employed to analyze and forecast univariate time series data. The SARIMA \((p,d,q)(P,D,Q)[S]\) model is a developed form of the ARIMA \((p,d,q)\) model that reflects the seasonal variation of the time series (Box et al. 2016).

In this paper, the ARIMA and SARIMA models were applied for SSL forecasting using the R software program (Hyndman & Khandakar 2008). For both studied rivers ARIMA and SARIMA models have shown better performance respectively for daily and monthly time scales (Table 1). Besides the fact that the SSL modeling of Lighvanchai resulted in better performance than the Upper Rio Grande, it should be noted that at the monthly time scale, due to the low value of \(E\) (<0.5) for the Upper Rio Grande, the proposed model could not make a good fit with the observed data. It seems that this lack of assurance in modeling is because of the existence of multi-frequency characteristics and inherent non-linear behavior of the phenomenon, which cannot be handled by uni-frequency analysis via the linear SARIMA model. It should be noted that although the SARIMA model is capable of detecting the major pattern of time series, the results showed that due to their inherent nature (single frequency analysis of the seasonality property); complex and multi-frequency time series, such as SSL, could not be efficiently modeled via the SARIMA model.

Considering that feature selection is a vital step in AI-based modeling, Correlation Coefficient (CC) and Mutual Information (MI) have been imposed to select the dominant features (Nourani et al. 2015).

For modeling via ANN and EANN, the past runoff and SSL observations up to \(p\) and \(q\) lag times \((Q_t, Q_{t-1}, \ldots, Q_{t-p} \text{ and } S_t, S_{t-1}, \ldots, S_{t-q})\) respectively were considered as potential input variables of ANN and EANN to forecast the value of SSL in one-step-ahead \((S_{t+1})\).

It should be emphasized that the efficiency of AI-based models is affected by appropriate selection of input variables, as well as correct adjustment of the network parameters such as the number of hidden neurons, transfer functions of layers and training iteration number. Activation functions smooth or normalize the output before it is passed on to the next or previous neurons in the chain. These functions help neural networks learn and improve themselves. Tangent sigmoid was considered as the activation function of the hidden layer and the output layer in this study. As mentioned before, the input data are normalized to become between 0 and 1 before feeding into the network. The tangent sigmoid function exists between 0 and 1 and is used in ANNs to introduce nonlinearity in the model. To train the ANN and EANN, the Levenberg–Marquardt BP method was utilized. The Levenberg–Marquardt algorithm is specifically designed to minimize sum-of-square error functions. In the Levenberg–Marquardt algorithm, the error function is minimized while the step size is kept small in order to ensure the validity of the linear approximation. This algorithm is an iterative technique that locates a local minimum of a multivariate function that is expressed as the sum of squares of several non-linear, real-valued functions. It has become a standard technique for non-linear least-square problems, widely adopted in various disciplines for dealing with data-fitting applications. Hormonal parameters as dynamic weights are initialized, then are adjusted over the training phase and recurrently give the feedback to the other components of the model.

The best results of ANN and EANN for the Lighvanchai and Upper Rio Grande Rivers have been presented in Table 2. For this purpose, up to quadruple of the inputs were considered as the hidden neurons and up to 500 were examined as epochs number. Finally, the best models were selected based on evaluation criteria. As seen, the hormonal parameters for daily models are greater than those for monthly modeling due to the fact that the daily time scale has a high stochastic characteristic.

To increase the efficiency of the used autoregressive models (i.e. ANN and EANNs), wavelet-based WEANN and WANN models with the ability to handle the multi-frequency features of the SSL time series were also applied for the modeling. In practice, hydrologists deal with discrete time signal phenomena rather than a continuous one. For more details about the corresponding formulas, the readers are referred to (Addison 2017; Sharghi et al. 2019).
<table>
<thead>
<tr>
<th>Rivers</th>
<th>Time scale</th>
<th>Models</th>
<th>Inputs</th>
<th>Structure</th>
<th>No. hidden neuron</th>
<th>Nash-Sutcliffe(E)</th>
<th>RMSE*</th>
<th>E peak Validation</th>
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<td>–</td>
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<td>0.581</td>
<td>7614.703 11309.290</td>
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<td></td>
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<td>10</td>
<td>6</td>
<td>50</td>
<td>7487.459 11045.08</td>
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<tr>
<td></td>
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<td>S(t-1),S(t-1),S(t-1),Q(t-1),Q(t-1)</td>
<td>5-5-1</td>
<td>9</td>
<td>5</td>
<td>30</td>
<td>4321.245 7263.256</td>
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<td>–</td>
<td>6</td>
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<td></td>
<td>Monthly</td>
<td>ARIMA</td>
<td>–</td>
<td>SARIMA(1,0,1)(1, 0, 2)[12]</td>
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<td>40</td>
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<td>5-4-1</td>
<td>9</td>
<td>4</td>
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<td>–</td>
<td>4</td>
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<td>6</td>
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<td>–</td>
<td>4</td>
<td>30</td>
<td>305.156 334.179</td>
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*The unit of RMSE is ton/day for daily time scale and ton/month for monthly time scale.
It is noteworthy to mention, a complete literature review of WT hydrological applications have been cited by Nourani et al. (2014). For this purpose, the dyadic discrete WT was used to extract the low and high frequencies of SSL time series in both daily and monthly time scales. By using the WT, each input time series is decomposed to \( i + 1 \) sub-series (one approximation sub-series and \( i \) detailed sub-series). It is notable that \( i \) represents the level of decomposition and each sub-series denotes a specific frequency of the seasonal characteristic of the input time series. Finally, by applying the feature selection methods to the decomposed sub-series and training network via the EANN and ANN models, the related output of each model, \( S(t + 1) \) can be predicted.

According to the previous studies, resolution levels of 2 to 5 for the monthly modeling and 2 to 8 for the daily modeling were examined initially, which respectively signify \( 2^2 \) – days/months mode, \( 2^3 \) – days (near a week)/months, \( 2^4 \) – days (near a semi month in the daily scale)/months and so on. Also, the db mother wavelet which is commonly used in hydrological modeling was used. Some previous studies have showed that since after decomposition by wavelet the ANN model can adjust the output, the type of mother wavelet, in contrast to decomposition level, does not have a significant impact on WANN modeling (Nourani et al. 2014). It is notable that the best results were obtained for the 4th decomposition level in both scales. Therefore, only the results of the 4th level are reported in Table 2.

The results summarized in Table 2 denote the superiority of the WEANN model over other applied models, of up to 42% and 14% in daily modeling and up to 141% and 87% in monthly modeling respectively for the Upper Rio Grande and Lighvanchai Rivers. Especially, WEANN could capture the peak values of SSL time series in a more efficient way than the other models in both rivers due to its hormonal (emotional) parameters, which handle the emotional conditions (e.g. peak states) of the model by acting as dynamic weights (see Table 2, Figure 2). As can be seen, the improvement of efficiency for the Upper Rio Grande River SSL modeling is greater than that of the Lighvanchai River utilizing different models at different time scales. This is maybe because of reasons including the bigger area of Upper Rio Grande watershed, wilder geomorphological conditions and, as a result, its strongly non-linear behavior, so the proposed hybrid models (WEANN and WANN) could appropriately model the process.

Numerical comparison of the summarized results in Table 2 indicates the fast training (low epochs number) of the WEANN model and its low number of hormones versus the EANN model. The simultaneous presence of hormones and pre-processing of data by WT reduced the hormones and epochs number of the WEANN model. Besides, due to the high stochastic characteristic of daily SSL time series, the daily modeling needs longer memory than monthly modeling (i.e. more input neurons than monthly modeling). Since the autoregressive and seasonal characteristics of the SSL data are more dominant features respectively in daily and monthly scales, first the WEANN and second the WANN, by the ability to cope with both autoregressive and seasonality characteristics (owing to the multi-frequency property), were more efficient than other autoregressive models including EANN and ANN or linear ARIMA and SARIMA (uni-frequency analysis models). That means the reason behind the superiority of the WEANN and WANN to others is related to the multi-resolution analysis ability of WT dealing with complex SSL processes. In other words, the WT decomposes the original signal into some sub-signals at certain scales, each representing an individual seasonal scale, and so, multi-seasonal features of the time series can be handled in the modeling procedure. This improvement is increased in the large-scale series (e.g. monthly time scale) due to its notable seasonal characteristics. It is notable that the obtained results indicate the superiority of the WEANN over the WANN (also EANN over ANN) model due to its EANN core, with a few hormonal parameters.

The main geological difference between the related watersheds is their area size, which has clearly shown its influence on the SSL modeling. As can be seen in Table 2, for all modeling procedures, the Lighvanchai River obtained better results. It is clear that the size of the watershed affects the modeling result; as just one station is selected as the presenter of the whole watershed, the smaller the area of the watershed, the better the results of the modeling. On the other hand, the Upper Rio Grande watershed has a more dense land cover. Thus, the sediment generation and transformation are more complicated in this watershed in comparison to that of Lighvanchai. The greater complexity
in SSL modeling means intermediacy of non-linear and multi-frequency seasonal components is a major part of the SSL signal, which is visible in the performance of the models in Table 2. Table 2 proves the priority of the WEANN model, which considers the non-linearity, non-stationary and multi-frequency behaviors of the signal in the modeling procedure.

CONCLUSIONS

In this work, the capability of SARIMA, ANN, WANN, EANN (a new generation of ANN models with a few hormonal parameters) and WEANN (a wavelet-based EANN model) were examined for daily and monthly SSL modeling of two rivers with different hydro-geomorphological and land cover conditions in the related watersheds. By comparison of the obtained results, it was revealed that using WT as a data pre-processing tool could lead to more accurate predictions of SSL. The obtained results indicate the superiority of the WEANN over the WANN (also EANN over ANN) model due to its EANN core, which contains a few hormonal (emotional) parameters that handle the emotional conditions (e.g. peak states) of the model by acting as dynamic weights that give feedback to the other components of the model recurrently. The WEANN could lead to superior performance with regards to the compared models of up to 42% and 14% in daily modeling and 141% and 87% in monthly modeling, respectively, for the Upper Rio Grande and Lighvanchai Rivers. Also, the WEANN performance in catching the peak values is significantly better than the other models.

Figure 2 | Observed versus computed SSL (a detail) and verification scatter plot at daily time scale for: (a,b) Lighvanchai River; (c,d) Upper Rio Grande River.
The improvement of modeling in the validation step for the Upper Rio Grande is higher than that of Lighvanchai. This is possibly a result of the fact that the higher heterogeneity of land cover (due to the larger area of the watershed) make the case study more complex. Also, in such a great area (>10,000 km²), storm events are more complex and irregular, so the irregularity of streamflow is increased and, as a result, the sedimentation process is more irregular and complex, affected by a series of seasonal components. Also, comparing two different hydro-ecological case studies with different land cover characteristics showed that the proposed model in this study is effective for SSL modeling of rivers with small characteristics. However, hydro-ecological case studies with different land cover in such a great area (>142 km²) and large (about 10,000 km²) related watersheds make the case study more complex. Also, this is possibly a result of the fact that the higher order of the Upper Rio Grande is higher than that of Lighvanchai.

Such reliable employment of WEANN in SSL modeling suggests its implementation for modeling other hydro-environmental (e.g. groundwater, precipitation, etc.) processes.

REFERENCES


