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Suspended sediment load prediction of river systems: An artificial neural network approach

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ABSTRACT

Information on suspended sediment load is crucial to water management and environmental protection. Suspended sediment loads for three major rivers (Mississippi, Missouri and Rio Grande) in USA are estimated using artificial neural network (ANN) modeling approach. A multilayer perceptron (MLP) ANN with an error back propagation algorithm, using historical daily and weekly hydroclimatological data (precipitation $P_{(t)}$, current discharge $Q_{(t)}$, antecedent discharge $Q_{(t-1)}$, and antecedent sediment load $SL_{(t-1)}$), is used to predict the suspended sediment load $SL_{(t)}$ at the selected monitoring stations. Performance of ANN was evaluated using different combinations of input data sets, length of record for training, and temporal resolution (daily and weekly data). Results from ANN model were compared with results from multiple linear regressions (MLR), multiple non-linear regression (MNLR) and Autoregressive integrated moving average (ARIMA) using correlation coefficient (R), mean absolute percent error (*MAPE*) and model efficiency (E). Comparison of training period length was also made (4, 3 and 2 years of training and 1, 2 and 3 years of testing, respectively). The model efficiency (E) and R^2 values were slightly higher for the 4 years of training and 1 year of testing (4 * 1) for Mississippi River, indifferent for Missouri and slightly lower for Rio Grande River. Daily simulations using Input 1 ($P_{(t)}$, $Q_{(t)}$, $Q_{(t-1)}$, $SL_{(t-1)}$) and three years of training and two years of testing (3 * 2) performed better (R^2 and E of 0.85 and 0.72, respectively) than the simulation with two years of training and three years of testing (2 * 3) (R^2 and E of 0.64 and 0.46, respectively). ANN predicted daily values using Input 1 and 3 * 2 architecture for Missouri ($R^2 = 0.97$) and Mississippi ($R^2 = 0.96$) were better than those of Rio Grande ($R^2 = 0.65$). Daily predictions were better compared to weekly predictions for all three rivers due to higher correlation within daily than weekly data. ANN predictions for most simulations were superior compared to predictions using MLR, MNLR and ARIMA. The modeling approach presented in this paper can be potentially used to reduce the frequency of costly operations for sediment measurement where hydrological data is readily available.

1. Introduction

Non-point source pollution including soil erosion, nutrient loading and associated pollutants pose a serious threat to the environment. It is estimated that annual economic damages from soil erosion are over $10 billion in the US (Lovejoy et al., 1997). More than 50% of the pollution entering the nation's water comes from non-point sources with agricultural and forested lands topping the list (EPA, 1990). Although considerable progress has been made in reducing point source pollution in the US since the passage of the Federal Water Pollution Control Act amendments in 1972, many water quality problems including suspended sediment persist due to runoff from non-point sources (Brown and Binkley, 1994). The network of rivers in the US is responsible for carrying large volumes of sediment and nutrients to the coastal waters. Sediments are increasingly recognized as an important part of fluvial ecosystems and estuarine wetlands responsible for the transportations of nutrients and pollutants.

Sediment load at the watershed outlets are caused by physical processes of detachment, transportation and deposition. The magnitude and concentration of sediment are mainly affected by precipitation (intensity and volume), physical properties of soil (texture and detachability), topography, and land cover (vegetation).

Sediment load information is useful for problems in the design of reservoirs and dams, transport of sediment and pollutants in rivers, lakes and estuaries, design of stable channels and dams, pro-

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tection of fish and wildlife habitats, determination of the effects of watershed management, and environmental impact assessment (Cigizoglu, 2004). Sediment modeling is also of great interest for those working at the interface of management and environment.

Water quality and sediment modeling have been a challenging task in the field of computational hydrology. Traditionally used methods (e.g., Ahmad et al., 2009, 2010) to determine runoff often do not take into account sediment load. Estimation of sediment load has been approached through empirical relationships, numerical simulations, physically based models, and using remote sensing and Geographic Information Systems (GIS) techniques. Anton et al. (2001) developed a spatially distributed model for the calculation of sediment delivery to river channels in central Belgium. The model consists of two components: (i) the calculation of a spatial pattern of mean annual soil erosion rates in the catchment using a Revised Soil Erosion Equation approach; and (ii) the routing of the eroded sediment to the river channel network. Results show that the model can predict sediment load for catchments up to 5000 ha with an average accuracy of 41%. De Roo (1998) reviewed several applications where GIS was used for modeling runoff and sediment transport. Mashriqui and Cruise (1997) coupled GIS with a geomorphic-based hydrologic and sediment transport model to estimate runoff and sediment in western Puerto Rico. Based on homogeneity of topography and soil characteristics they used "grouped response unit" for modeling.

Babel et al. (2004) used an Agricultural Non-Point Source (AGNPS) model to estimate runoff volume, sediment, and nutrient load due to agricultural activities in the Huai Nong Prong watershed in Southeastern Thailand. For the ten rainfall events simulated, the coefficient of performance was 0.09, 0.47, 0.09, and 0.03 for runoff volume, sediment load, total nitrogen, and total phosphorus, respectively. Arnold et al. (1995) developed a continuous model to estimate water and sediment load. They tested the model on three different spatial scales: ARS station G (17.7 km^2) at Riesel, Texas, White Rock Lake watershed (257 km^2) near Dallas, and the Lower Colorado River basin (9000 km^2). Kothyari et al. (1996) used the time–area curve of a catchment for predicting the variation of sediment load with time. They considered that sediment delivery ratio in a catchment is a function of land slope, area, and extent of forest covers. Singer and Dunne (2001) evaluated the suspended sediment budget for the Sacramento River. They employed time series analysis to quantify the relationship between streamflow and suspended sediment concentration for gauging stations along the main channel and the contributing tributaries. Sediment concentration records of 2-yr duration were extended using Box-Jenkins transfer function models to calculate annual rates of suspended sediment discharge over a 32-year period.

Bhuyan et al. (2002) used Landsat Thematic Mapper (TM) images, ArcInfo, and AGNPS model to assess runoff and sediment load from various sub-watersheds above the Cheney Reservoir in Kansas. They found that the modeling process was only effective for small watersheds (up to 145 km^2) with adequate available rainfall data. Miller and Cruise (1995) used multispectral data acquired from the Calibrated Airborne Multispectral Scanner (CAMS) and the Landsat TM to estimate suspended sediments discharged from three rivers into Mayaguez Bay, Puerto Rico. They produced spatial maps of suspended sediment concentrations in Mayaguez Bay during low to moderate discharge for 1990–1992.

The spatial heterogeneity of various physical, hydrometerological and geomorphologic properties of river basins and the non-linear relationship between these variables and the sedimentation process has been a major obstacle in accurately predicting sediment load and concentration. The use of physical and conceptual models requires detailed topographic, eco-hydro-climatological and geophysical information (Ahmad and Simonovic, 2006; Mosquera-Machado and Ahmad, 2007). Preparation of such information for large river basins like that of Mississippi and Missouri will be difficult and costly. Alternative approach to the existing process and physical-based sediment models is the use of machine learning techniques capable of predicting the output function using a properly designed input function.

Bhattacharya et al. (2003) explained machine learning as an interdisciplinary subject, which is enriched with concepts drawn from diverse fields such as statistics, artificial intelligence, information technology, biology, cognitive science, and control theory. Machine learning includes methods such as artificial neural networks (ANNs) and is aimed at developing learning technique through pattern recognition that can learn from data and forecast outputs such as sediment load.

ANNs have been used for a wide range of different learning-from-data applications and input–output correlations of non-linear processes. Various researchers have used ANNs for hydrologic studies including time series predictions of runoff or flow (Hsu et al., 1995; Shamseldin, 1997; Zealand et al., 1999; Tingsanchali and Gautam, 2000; Imrie et al., 2000; Cigizoglu, 2005; Melesse and Wang, 2006), water table management (Yang et al., 1998), estimation of runoff hydrograph parameters (Ahmad and Simonovic, 2005), reservoir operation optimization (Solomatine and Torres, 1996), water quality management (Wen and Lee, 1998), estimating water quality parameters (Zhang and Stanley, 1997; Melesse et al., 2008), non-point source contamination (Brion and Lingireddy, 1999), sediment prediction (Abrahart and White, 2001; Nagy et al., 2002; Yitian and Gu, 2003; Cigizoglu, 2004; Cigizoglu and Kisi, 2006; Alp and Cigizoglu, 2007; Cigizoglu and Alp, 2006) and other applications in water resources (ASCE Task Committee, 2000; Cigizoglu, 2003a,b; Jain et al., 1999; Maier and Dandy, 2000; Sudheer, 2005; Sudheer and Jain, 2004).

For complex hydrologic systems or non-linear modeling applications, where physically based models do not perform well, ANNs have proven to be useful. One limitation of ANN is the need for longer time series data for training and testing. It is evident from literature review that for watersheds with longer time series data, ANN has worked very well. In the United States, longer time series of data is available for networks of rivers which makes the ANN approach suitable for its application.

The use of ANN in sediment modeling in the above mentioned studies has certain limitations, for example very few of the studies consider precipitation in the neural network architecture. In this study, we use an ANN approach to predict daily and weekly sediment load for three major river systems in the US (Mississippi, Missouri and Rio Grande). The study experiments with three different combinations of input data sets, different length of records for training and different temporal (daily and weekly) simulations. The model output is evaluated using statistical indices and observed sediment data. Comparison of the ANN model results to that of multiple linear regressions (MLR), multiple non-linear regression (MNLR) and Autoregressive integrated moving average (ARIMA) are also presented.

2. Study area and data sets

2.1. River systems

In this study, three major rivers of USA (Mississippi, Missouri and Rio Grande) are considered (Fig. 1).

The Mississippi River originates from northwestern Minnesota and flows to the Gulf of Mexico in Louisiana. The river is 3765 km long, and the major land uses are urban and agriculture in its drainage area. Including its tributaries, it drains 4.76 million km^2, which is about 40% of the contiguous United States. The upper Mississippi River basin has been repeatedly impacted by glacial ice during the last 2.5–3.0 million years. The continental glaciers