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Performance comparison of Adoptive Neuro Fuzzy Inference System (ANFIS) with Loading Simulation Program C^{++} (LSPC) model for streamflow simulation in El Niño Southern Oscillation (ENSO)-affected watershed

Suresh Sharma [a,*], Puneet Srivastava [b,1], Xing Fang [c,2], Latif Kalin [d,3]

[a] Civil and Environmental Engineering Program, Youngstown State University, Youngstown, OH 44555, United States
[b] Biosystems Engineering Department, Auburn University, Tom E. Corley Building, Auburn, AL 36849, United States
[c] Civil Engineering Department, Auburn University, 229 Harbert Engineering Center, Auburn, AL 36849, United States
[d] School of Forestry and Wildlife Sciences, Auburn University, Forestry and Wildlife Building, Auburn, AL 36849, United States

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ABSTRACT

Suitable selection of hydrological modeling tools and techniques for specific hydrological study is an essential step. Currently, hydrological simulation studies are relied on various physically based, conceptual and data driven models. Though data driven model such as Adoptive Neuro Fuzzy Inference System (ANFIS) has been successfully applied for hydrologic modeling ranging from small watershed scale to large river basin scale, its performance against physically based model has yet to be evaluated to ensure that ANFIS are as capable as any physically based model for simulation study. This study was conducted in Chickasaw Creek watershed, which is located in Mobile County of South Alabama. Since adequate rain gauge stations were not available near the watershed proximity, and also the study area was affected with the El Niño Southern Oscillation (ENSO), the sea surface temperature (SST) and sea level pressure (SLP) were additionally incorporated in the ANFIS model. The research concluded that ANFIS model performance was equally comparable to a physically based watershed model, Loading Simulation Program C^{++} (LSPC), especially when rain gauge stations were not adequate. Additionally, the research concludes that ANFIS model performance was equally comparable to that of LSPC no matter whether SST and SLP in ANFIS input vector was included or not.

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1. Introduction

Hydrologic modeling is essential for various water resources study including streamflow forecast, water uses scenarios, climate change impact on water resources. Selection of suitable hydrologic modeling approach has always been a vital issue because the suitability of modeling tools and techniques depends on the various elements. Since hydrologic simulation is a complex procedure and associated with large number of watershed parameters, several methods of modeling including process based, conceptual and data driven modeling approach have been experimented in diverse watershed conditions and reported in various articles (Clarke, 1973). Even though different studies in the past have reported that neither of these approaches is considered superior (Jayawardena, Muttil, & Lee, 2006), data-driven models such as artificial neural network (ANN) (Cochocki & Unbehauen, 1993; Committee, 2000; Tokar & Johnson, 1999) and the fuzzy logic approach (Zadeh, 1965) have been widely accepted and applied for hydrological modeling and various water resources studies (Sharma, 2012; Taheri Shahraiyni, Ghafouri, Saghafian, & Bagheri Shouraki, 2013; Tayfur, Ozdemir, & Singh, 2003; Tayfur & Singh, 2006) due to their simplicity and user friendly nature.

Over the years, researchers have found limitations of the conventionally adopted data-driven models as well. Therefore,

* Corresponding author. Tel.: +1 (330) 941 1741.
E-mail addresses: ssharma06@ysu.edu (S. Sharma), srivapu@auburn.edu (P. Srivastava), xing.fang@auburn.edu (X. Fang), kalinla@auburn.edu (L. Kalin).
[1] Tel.: +1 (334) 844 7426.
[2] Tel.: +1 (334) 844 8778.
[3] Tel.: +1 (334) 844 4671.

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researchers have started combining both techniques to overcome the limitations of individual models, and hence develop powerful intelligent systems. As a matter of fact, Neuro-Fuzzy system such as Adaptive Neuro-Fuzzy Inference System (ANFIS) (Jang, 1993) has been evolved and widely used.

Nevertheless, the hydrologic modeling in ANFIS also relies on the accuracy of input data, especially precipitation. Even though precipitation is the most sensitive input for hydrological modeling (Trenberth & Shea, 1987), majority of the hydrological models suffer from the adequate representation of spatial variability of the precipitation data, as the sufficient network of rain gauge locations needed for hydrological modeling are not frequently available (Sharma, Isik, Srivastava, & Kalin, 2012). In these circumstances, even a highly advanced, physically based model, which are capable to represent the watershed complexity in terms of land use, slope and soil may not be able to simulate streamflow with satisfactory model performance. Therefore, evaluations of proper modeling approach for a watershed with inadequate rain gauge stations are needed.

Although several studies in the past compared the performance of physically based models with data driven models in various watershed conditions (Makkeasorn, Chang, & Zhou, 2008; Morid, Gosain, & Keshari, 2002; Talei, Chua, & Quek, 2010; Wang, Skahill, Samaitis, & Johnston, 2002), only few studies have been conducted in a watershed characterized with limited rain gauge stations. In order to better represent the precipitation in the model, few studies in the past have been conducted to surrogate the lack of precipitation data by using sea surface temperature (SST) and sea level pressure (SLP) of the equatorial pacific in data driven models (Khalil, McKee, Kemblowski, & Asefa, 2005; Sharma, 2012; Tech & Center, 2009). The Changes in SST and SLP in the equatorial pacific has a potential to bring local and global climate variation (Ropelewski & Halpert, 1986). Since El Niño Southern Oscillation (ENSO), which is measured in terms of SST and SLP, has significant potential teleconnection with temperature, precipitation and streamflow in various regions (Barsugli, Whitaker, Loughe, Sardeshmukh, & Toth, 1999; Chiew, Piechota, Dracup, & McMahon, 1998; Hansen, Jones, Irmak, & Royce, 2001; Keener, Ingram, Jacobson, & Jones, 2007; Kulkarni, 2000; McCabe & Dettinger, 1999; Pascual, Rodó, Ellner, Colwell, & Bouma, 2000; Piechota & Dracup, 1996; Rajagopalan & Lall, 1998; Roy, 2006), SST and SLP can be directly applied in data driven models for streamflow simulation in ENSO affected watershed if the rain gauge stations in watershed proximity are scarce (Sharma, Srivastava, Fang, & Kalin, in press). However, conceptual or physically based watershed model are not capable to incorporate SST and SLP as inputs in their input vectors. Since the data driven model provides a unique opportunity for additional fusion of variables, several variables including SST, SLP and trade wind index, which are responsible to bring precipitation variation, can be additionally utilized as model inputs in data-driven models. This is especially true for ENSO-affected watersheds. Therefore, additional forcing of these variables may be beneficial particularly for watersheds which are significantly affected by ENSO, and also lack adequate rain gauge stations. In this context, this study was unique from various past studies in two ways; (i) it compared the two modeling approach particularly in ENSO affected watershed with inadequate rain gauge stations, (ii) it utilized the data from equatorial pacific to develop data-driven model, and compared its performance with physically based model. The objective of this research was to incorporate SST, SLP in ANFIS model, and evaluate the ANFIS model performance against a physically based, watershed model, Loading Simulation Program C^{++} (LSPC), for streamflow simulations in Chickasaw Creek watershed, which was affected by ENSO and characterized with inadequate rain gauge stations.

2. Theoretical considerations

ENSO is a coupled oceanic and atmospheric phenomenon which operates at interannual time scales resulting due to the complex interaction of oceanic (oceanic temperature and oceanic currents) and atmospheric (cloud, storms and winds) phenomenon (Kessler, 2002). ENSO is induced due to the sea surface temperature gradient and sea level pressure difference along the equatorial pacific. Various ENSO indicators such as SST and SLP are used to measure the ENSO Phenomenon.

2.1. ANFIS

Recently, scientists are more interested in using combined approaches, such as ANFIS which combines artificial neural network with fuzzy logic approaches. Due to its capability of combining the qualitative aspects of a fuzzy system with the quantitative aspect of a neural network, ANFIS has been found to be a more efficient modeling tool than the two independent models (i.e., ANN and fuzzy logic) to capture inherent non-linear processes (Jang, 1993). Hence, this model has been extensively applied in hydrological (Mukerji, Chatterjee, & Raghuwanshi, 2009; Pramanik & Panda, 2009) and water quality modeling (Yan, Zou, & Wang, 2010).

ANFIS is a multi-layer and feed-forward network, that is, the network is constructed in such a way that the nodes are not connected to the same layer but connected to the next layer which finds relationship of an input vector to an output layer. A standard ANFIS model structure using two inputs and one output is shown in the Fig. 1, which shows five layers with two rules and two membership functions (MFs) associated with each input.

The ANFIS model consisting two fuzzy if-then rules can be written as follows:

$$\text{Rule 1}: \text{If } X \text{ is } u1 \text{ and } Y \text{ is } v1, \text{then } f1 = p_1X + q_1Y + r_1 \tag{1}$$

$$\text{Rule 2}: \text{If } X \text{ is } u2 \text{ and } Y \text{ is } v2, \text{then } f2 = p_2X + q_2Y + r_2 \tag{2}$$

where u and v are the MFs for input X and Y, respectively. Similarly, p_1, q_1, r_1 and p_2, q_2, r_2 are the parameters which are needed to be ascertained for the output function. The operation of ANFIS model from layer 1 to layer 5 is briefly borrowed from Sharma et al. (in press) and presented here.

Layer 1 In this layer, input is given from each node and external signal is passed to the next layer.

Layer 2 In this layer, every node is termed as a membership function. For example, $\mu_{ui}(X)$ represents the membership function for input X which varies from 0 to 1.

Layer 3 In this layer, the incoming signals are multiplied and the product is forwarded to the next layer. Each output from a node characterizes a result of the predecessor (firing strength) of that rule. The outputs of this layer (O_i^3) can be written as follows.

$$O_i^3 = Z_i = \mu_{ui}(X)\mu_{vi}(Y), \quad \text{for}(i) = 1, 2 \tag{3}$$

where u and v represents the membership function for X and Y inputs, respectively.

Layer 4 In this layer, normalized firing strength is determined in each node using following equation.

$$O_i^4 = \overline{Z}_i = \frac{z_i}{z_1 + z_2} \tag{4}$$

where i = 1, 2.

Layer 5 In this layer, the following equation is used to compute the model output using the input contribution of each ith rule.