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

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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.

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; Taberi Shahrarayi, Ghafoori, Saghaian, & 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,
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 inadequate 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, Samailitis, & 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; Rajagopolan & 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 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, & Rahguwanshi, 2009; Framanik & 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:

Rule 1: if X is u1 and Y is v1, then f1 = p1X + q1Y + r1 (1)

Rule 2: if X is u2 and Y is v2, then f2 = p2X + q2Y + r2 (2)

where u and v are the MFs for input X and Y, respectively. Similarly, p1, q1, r1 and p2, q2, r2 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, μu(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 normalized firing strength is determined for each node characterizing a result of the predecessor (firing strength) of that rule. The outputs of this layer (O^l_3) can be written as follows.

\[ O^l_3 = Z_i = \mu_u(X)\mu_v(Y) \quad \text{for } (i) = 1, 2 \] (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.

\[ O^l_4 = Z_i = \frac{Z_i}{Z_1 + Z_2} \] (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.
\[ O_i^6 = \sum_{j=1}^{2} \frac{Z_i f_j}{Z_i} \]

where \(Z_i\) is the output from layer 3 and \(\{p_j, q_j, r_j\}\) are the model parameters.

Layer 6 In this layer, the final output is determined by combining entire receiving signals

\[ O_i^6 = \sum_{j=1}^{2} Z_i f_j = \frac{\sum_{j=1}^{2} Z_i f_j}{\sum_{j=1}^{2} Z_i}. \]

Finally, ANFIS model uses hybrid algorithm to compute the model parameters. To effectively partition the data and minimize the fuzzy rules, various clustering approach have been recommended. Two widely used fuzzy clustering method such as subtractive clustering algorithm (SCA) (Chiu, 1996) and Fuzzy C-Mean (FCM) (Dunn, 1973) for structure identification has been described in the following section.

2.1.1. Subtractive and Fuzzy C-Mean clustering

For large and good quality data sets covering the wide variations in the feature space, fuzzy systems can have better generalization due to the use of more fuzzy rules. However, for a small range of data sets, which is more common in streamflow data sets, large number of rules cannot be derived from the training data as it may easily over fit the system, and rule out the possibility of generalization. Hence, clustering approach is required for both the effective partition of the input space and the reduction of the number of rules. Several clustering methods have been suggested to organize the data and construct the rules. Some of the widely used approaches are grid partition (Jang & Sun, 1995), SCA, and FCM. In this analysis, both FCM and SCA were experimented. FCM is a technique in which each data point is categorized into a cluster based on membership function (Thirumalaiash & Deo, 2000). It divides the data from multidimensional space into a particular cluster number. Cluster center and the membership function were decided through the repeated iteration by minimizing the objective function which was defined as a distance between data point and cluster center. SCA is more suitable when users do not have a clear idea of cluster number required to be used for a given data sets. This algorithm is based on the amount of the density points in the data space, and the approach is to find areas in the data space having higher densities of data points. The algorithm tries to find the point with the highest number of neighbors as the center of the cluster. For a given set of data points from \(X_1, X_2, \ldots \ldots \) to \(X_n\), the density measure at a data point \(X_i\) is given by the following equation:

\[ d_j = \sum_{j=1}^{n} e^{-\frac{\|X_i - X_j\|^2}{(2\sigma^2)}} \]

where \(\sigma\) is a data cluster radius. The equation indicates that those data points which have high neighboring data points will be considered as a cluster center.

2.2. LSPC model

The LSPC, a C++ version of the widely used Hydrologic Simulation Program Fortran (HSPF) (Bicknell et al., 2001), is a watershed model for simulating streamflow and stream hydraulics. Though the LSPC’s algorithms are identical to those of the HSPF, LSPC model is more efficient, flexible and have been used for streamflow and water quality simulation (e.g. Sharma, Srivastava, Kalin, Fang, & Elias, 2014). The model has been considered as one of the most advanced hydrologic and watershed loading model. The hydrologic portion of the model is based on the Stanford Watershed Model (Crawford & Linsley, 1966). The hydrologic process in the model is conceptualized with the schematic diagram as shown in Fig. 2 (Tech & Center, 2009). The diagram shows the water budget diagram with the water interchanging process from surface to subsurface including three flow path; surface, interflow and groundwater flow.

Precipitation is the input to the system (watershed) which is partitioned at the first decision node for the interception and water reaching on the land surface using the parameter CEPC (Fig. 2). In the next decision node, surface and lower zone storage is divided using the parameter, INFILT. The surface storage contributes to the three components: (i) upper zone storage which partly contributes to lower zone, partly to the groundwater/inactive groundwater storage, and rest to the evapotranspiration (ET), (ii) interflow storage, which eventually contributes to the channel flow, (iii) overland flow. The lower zone storage may partly contribute to groundwater storage or inactive groundwater storage (deep percolation) or partly lost through ET. The contribution from upper zone and lower zone storage to groundwater is divided into active and inactive groundwater by using a coefficient (DEEPFR). Active groundwater storage can contribute to streamflow as base flow.
and losses as ET. ET can occur from the entire zone except inactive groundwater zone. The overland flow, interflow, and base flows eventually contribute to streamflow.

3. Study site

This research was conducted in Chickasaw Creek watershed (Fig. 3) which is located in Mobile County of Southern Alabama in the Mobile River Basin of Southeast USA. The watershed is primarily in coastal region but starts at Citronelle in North, drains into Mobile Bay in South, and ultimately discharges to the Gulf of Mexico. The watershed drainage area is 714 km$^2$, and is characterized by dense residential, forest, agricultural and industrial land uses. The characteristics of the watershed have been dominated by the coastal plain geology with highest elevation range of 13.11 m and lowest 0 m above the mean sea level. The region is characterized with higher rainfall, i.e. the average annual precipitation in the watershed is fairly higher (1651 mm) than average annual precipitation of the Alabama. The precipitation and temperature of this region is associated with ENSO, characterized with fairly higher precipitation and lower temperature in El Niño winter, and just opposite pattern in La Niña winter (Sharma, Srivastava, Fang, & Kalin, 2012). The long term recorded data starting since 1950 including SST, SLP in Tahiti and Darwin (Kessler, 2002) and trade wind index (Lukas, Hayes, & Wyrtki, 1984), were downloaded from NOAA’s NCDC and National Center for Environment Prediction (NCEP). These data corresponds to the Niño 3.4 region ($5^\circ$N to $5^\circ$S, 120$^\circ$W to 170$^\circ$W) (Trenberth & Stepaniak, 2001) located in the equatorial pacific and presented in Table 1.

5. Methodology

5.1. Parameter estimation

Using the generic model structure as described in Fig. 1, the ANFIS model was developed considering several other inputs. The model development is borrowed from Sharma et al. (in press) and briefly presented in this article having two inputs with two rules for illustration. In fact, this model has been extended for numerous input variables and implemented in our research. In this study, streamflow (SF) is assumed to be a function of SST, SLP, temperature (T) and precipitation (PCP). That is, $\text{SF} = f(\text{SST}, \text{SLP}, \text{T}, \text{PCP})$. Considering $\mu_1, \mu_2$ and $\nu_1, \nu_2$ were the corresponding membership functions for two input variables (T and PCP) and $a_1, b_1, a_2, b_2$ were the associated model parameters, model output can be determined as linear combinations of consequential parameters. The following equation can predict streamflow ($\text{SF}_t$) as model output for a given time $t$.

$$\text{SF}_t = (w_1T)a_1 + (w_1\text{PCP})b_1 + w_1\tau_1 + (w_2T)a_2 + (w_2\text{PCP})b_2 + w_2\tau_2$$

Fig. 2. Schematic diagram of the Stanford Watershed Model adapted for LSPC model. Number corresponding to each circle denotes the order of removing water to satisfy ET. (Source: Tech & Center, 2009). INFILT, infiltration parameter; INTFW, interflow parameter; CEPSC, interception storage capacity; LZZN, lower zone storage capacity; UZZN, upper zone storage capacity; NSUR, Manning’s surface roughness; LLSUR, surface runoff length; SLSUR, surface slope; IRC, interflow recession constant; AGWETP, active groundwater ET parameter; AGWRC, active groundwater recession; BASETP, base flow ET parameter; DEEPFR, fraction to inactive groundwater; LZETP, lower zone ET parameter.
Equations to predict the streamflow time series \((SF_1, SF_2, \ldots, SF_n)\) can be arranged in matrix form as follows:

\[
A = \begin{bmatrix}
W_1T_1 & W_1PCP_1 & W_1 & W_2T_1 & W_2PCP_1 & W_2 \\
W_1T_2 & W_1PCP_2 & W_1 & W_2T_2 & W_2PCP_2 & W_2 \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\
W_1T_n & W_1PCP_n & W_1 & W_2T_n & W_2PCP_n & W_2
\end{bmatrix}
\]

where \(O\) is a matrix of unknown model parameters which can be determined by solving the following equation.

\[
O = \left( A^T A \right)^{-1} A^T Z
\]

where \(A^{-1}\) and \(A^T\) are the inverse and the transpose of the matrix “\(A\)”, respectively. ANFIS uses hybrid algorithm to solve this matrix. Hybrid algorithm (Jang, Sun, & Mizutani, 1997) is a combination of least-square method and back propagation algorithm which trains the data fairly rapid with speedy convergence. Readers can find detail mathematical description of the hybrid approach in various articles (Jang, 1993).
5.2. Input data

Appropriate selections of suitable membership function with proper number of fuzzy rules were essential for ANFIS model development. Selection of appropriate and optimum number of inputs is needed in fuzzy inference system for effective mapping of the input and output relationship. Therefore, correlations of several relevant inputs with the outputs were examined.

Since streamflow is a collective form of quick response (surface runoff) and the slow response (baseflow) of the watershed, it is always essential to separate the streamflow into surface runoff (SR) and baseflow (BF) components in order to adequately represent the watershed characteristics. Hence, we used baseflow filter program (Lim et al., 2005) to partition the streamflow. There are many reasons of baseflow separation. For example, BF is linked with the precipitation of previous time steps whereas SR is entirely contributed by precipitation of the current time step. Recursive Digital Filter method was utilized to develop the separate SR and BF data sets and corresponding models from given streamflow data. The input variables for SR and BF models are listed in Table 2. The model inputs for SR were temperature, SST, SLP and "estimated surface runoff" at different time step (Table 2), where "estimated surface runoff (SRt)" was determined using SCS curve number equation (Bosznay, 1989). The parameter needed for SCS curve number equation including curve number and hydrological soil groups were estimated based on the 2001 land cover data set (NLCD, 2010), and the SSURGO soil (SSURGO, 2010) database, respectively. However, the model inputs for BF model were simply SST, SLP, temperature and precipitation of various time step (Table 2).

In fact, Optimum sets of best inputs were decided after evaluating the parameter significant test in multiple linear regressions (MLR) model. Since precipitation and temperature were affected by SST and SLP, we wanted to evaluate whether all these inputs at various lead times were statistically significant (P-value <0.1). The analysis depicted that both SST and SLP were statistically significant for the seasons, when ENSO had a distinct signature with streamflows especially for winter and spring. Inputs having no significant contribution for the improvement of model performance were ignored.

5.3. ANFIS model development

After investigating optimum inputs, ANFIS models were developed for SR as well as BF. In addition, ANFIS models, without SST and SLP in their input vectors, were developed to identify the differences in model simulation with and without SST and SLP. Since we wanted to evaluate model performance in daily scale, ANFIS model was extended to a daily scale after experimenting with further input datasets. We did not find considerable difference in inputs for SR model whether we simulate in monthly or daily scale. However, inputs for base flow in daily scale were different to that of monthly scale. This is mainly because the current level of base flow may rely on the precipitation pattern that was encountered immediately few days or week ahead due to delay in groundwater contribution. Therefore, the best sets of inputs for baseflow simulation in daily and monthly simulation were different.

The ANFIS models were developed using 50 years of observed data. The data were segregated into model training (80%), validation (10%) and testing (10%). Initially, both FCM and SCA were experimented for clustering the data. Finally, we found that SCA was more suitable to cluster the given datasets. Parameters needed for SCA clustering including the membership function, range of influence of the cluster center, acceptance and rejection ratio were determined through a recurrent trial and error method by minimizing the root mean square error and maximizing $R^2$.

Similarly, suitable numbers of epochs required for ANFIS model training were optimally decided using trial and error from the visual inspection of error curve for training and validation. The overtraining of the data was eluded by evaluating its performance against checking data sets and controlling proper epoch number.

5.4. Performance evaluation

The performance of ANFIS model was evaluated through $R^2$ (coefficient of determination), Nash-Sutcliffe efficiency, NSE (Nash & Sutcliffe, 1970), mass balance error (MBE), and the root mean square error (RMSE). The detail descriptions about the modeling protocols (Engel, Storm, White, Arnold, & Arabi, 2007) statistical parameters to measure the model performance are available in many articles (Moriasi et al., 2007). Additionally, the performance of the ANFIS model was further compared with another independent watershed model, LSPC (Shen, Parker, & Riverson, 2005; Tech & Center, 2009).

5.5. Comparison with LSPC model

The modeling paradigms in two models, ANFIS and LSPC, are completely different. ANFIS is based on the learning approach, which is accomplished through model training between the known set of association between inputs and output data sets, whereas, LSPC is based on physical processes related with rainfall input and its transformation into runoff at the watershed outlet. The brief description of the LSPC model application in Chicksaw Creek watershed is explained in the following section.

5.6. LSPC model configuration

Hydrological processes in LSPC model are governed by certain hydrological parameters. Watershed parameters such as length, slope, stream network and sub-watershed area were determined through the interactive watershed delineation using high resolution (10 m) Digital Elevation Model (DEM)(DEM, 2010). Land use and soil-related parameters were extracted using Land cover data set of year 2001 (NLCD, 2010) and high resolution soil data (SSURGO) (SSURGO, 2010), respectively. LSPC model was configured to simulate a series of hydrologically connected sub-watersheds, with defined geometry, soil and land use characteristics. Each sub watershed area contributed runoff to their respective reach, where the cumulative flow was routed downstream to the watershed outlet. LSPC model utilizes different sets of hydrologic parameters for surface and subsurface hydrologic analyses in different sub watersheds based on the soil type and land use categories. Chicksaw Creek watershed was predominantly characterized by hydrological soil groups A, B and D. The watershed land cover was dominated by forest. The land use was classified as low, medium, and industrial urban (13%), deciduous, evergreen and mixed forest (47.4%), woody and herbaceous wetland (18.6%), range shrubland, grassland herbaceous and hay (19.4%), and the rest as water, south western range and agricultural land (1.6%).

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**Table 2**

<table>
<thead>
<tr>
<th>Model</th>
<th>Input variables used</th>
</tr>
</thead>
<tbody>
<tr>
<td>SR Model</td>
<td>SST(t-1), SLP(t), T(t-1), P(t-1), SR(t-1), SR(t)</td>
</tr>
<tr>
<td>BF Model</td>
<td>SST(t), SLP(t), T(t-1), P(t-1), P(t)</td>
</tr>
</tbody>
</table>

Note: SRt, T(t), P(t), and SST(t) denote "estimated surface runoff", temperature, precipitation, sea surface temperature, and sea level pressure difference between Tahiti and Darwin at the month “t”; respectively.
The information about the land use data, soil data and USGS gage is reported in Table 2.

5.7. Hydrologic model calibration and validation

The hydrologic model calibrations were carried out using the observed streamflow recorded from 1/1/1990 to 12/31/1996 at a USGS gage station (station ID02471001). Since 2001 land cover data sets were used, the calibrated model parameters were applied to an independent time period (1/1/1997–12/31/2002) for model validation. This period was selected as a validation period to evaluate the model performance for the latest land use condition. The simulation was started from 1/1/1985, permitting long spin up period for the model in order to minimize the effect of unknown initial moisture conditions, and to stabilize the hydrological conditions.

The watershed parameters, difficult to measure, were calibrated within a physically possible range, through the repeated trial and error procedure until the simulated streamflows closely approximated with the observed streamflows. The model parameters adjusted during hydrologic model calibration are presented in Table 3. Once the model was calibrated and validated, the model was run for another 40 years to simulate the long term streamflow. LSPC was run in hourly time step, and simulated flows were aggregated into daily and monthly time scale for model comparisons by computing corresponding statistical error parameters.

Once the LSPC model was simulated for long term, we compared the performance of LSPC model with ANFIS in different ENSO events. ANFIS models was compared with LSPC model in two ways. In the first step, ANFIS model was developed using long term dataset starting since 1950, and its performance was compared with the same consecutive period of LSPC model calibration and validation. In other words, ANFIS model was developed from the long term datasets but ANFIS simulated result from 1990 to 2002, which is a period of LSPC model calibration and validation was compared with LSPC model performance. In the second step, ANFIS model was developed with same period of datasets from 1990 to 2002, a period of LSPC model calibration and validation. This was mainly because we wanted to see the response of ANFIS model for shorter-term datasets and make realistic comparison with the LSPC model using datasets of the same period. In addition, we wanted to test the performance of ANFIS model without SST and SLP. For this, we removed the SST and SLP from its input vector. The model performance excluding SST and SLP was compared with the model performance including SST and SLP.

6. Result and discussion

6.1. Model performance

6.1.1. ANFIS

Table 4 shows the ANFIS model performance for streamflow simulation (combined SR and BF) compared with observed data. The ANFIS model performance was consistently better in all stages of training, validation, and testing with reasonable accuracy (Fig. 4), as indicated through the visual inspection of the observed and simulated streamflow time series. Additionally, the ANFIS model was simulated to a daily scale, separately for SR and BF. Table 5 shows the ANFIS model performance for combined SF simulation in a daily scale. Our analysis indicates that that SLP, SST and SST(t-1) were the sensitive inputs in daily scale as well.

6.1.2. LSPC

The performance of the LSPC model was promising for monthly simulation and satisfactory for daily simulation demonstrating that hydrological parameters were able to capture the dynamics of the system. The following section further compares the performance of the LSPC model with the ANFIS Model.

6.2. Model comparison

Model results after calibration were assessed through the comparison of simulated and observed streamflow in terms of water budget, storm flow comparison with respect to volume and peak, low flow and high flow period (Table 6), etc. The statistical parameters, such as, NSE, R² and MBE are listed in Table 7. The comparisons of observed and simulated streamflow from calibrated and validated LSPC are shown in Fig. 5 and Fig. 6, respectively. LSPC model performance during calibration and validation period is also compared with the ANFIS model (Figs. 5 and 6). Even though ANFIS model was developed using long term datasets from 1950, the two model performance was compared for the same period of model simulation. That is, we used ANFIS simulated streamflow from 1990 to 2002 to compare with the LSPC model calibration (1/1/1990–12/31/1996), and model validation (1/1/1997–12/31/2002) period. The model comparisons in those consecutive periods suggested that the performance of the ANFIS model was comparable to the performance of the LSPC model (Table 7).

Table 3

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Units</th>
<th>Typical Value</th>
<th>Calibrated Value</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>LZSN</td>
<td>Lower zone nominal soil moisture storage</td>
<td>Inches</td>
<td>2.0–15.0</td>
<td>9</td>
<td>An increase will provide more chances for ET and decreases flow</td>
</tr>
<tr>
<td>INFILT</td>
<td>Index to infiltration capacity</td>
<td>Inches hr⁻¹</td>
<td>0.001–0.50</td>
<td>0.01–0.08</td>
<td>An increase will cause shift of surface runoff to base flow</td>
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<tr>
<td>KVARY</td>
<td>Variable ground water recession</td>
<td>Inch⁻¹</td>
<td>0.0–0.5</td>
<td>0.25</td>
<td>An increase will cause quick ground water depletion</td>
</tr>
<tr>
<td>AGWRC</td>
<td>Base ground water recession</td>
<td>None</td>
<td>0.850–0.999</td>
<td>0.992–0.998</td>
<td>An increase will cause the flattened base recession</td>
</tr>
</tbody>
</table>

Table 4

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Streamflow Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE (m³/s)</td>
<td>2.63</td>
</tr>
<tr>
<td>NSE</td>
<td>0.8</td>
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<tr>
<td>MBE</td>
<td>0%</td>
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Table 5

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<thead>
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<th>ANFIS</th>
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</thead>
<tbody>
<tr>
<td>RMSE (m³/s)</td>
<td>9.9</td>
<td>7.0</td>
</tr>
<tr>
<td>NSE</td>
<td>0.49</td>
<td>0.68</td>
</tr>
<tr>
<td>MBE</td>
<td>2%</td>
<td>0.6%</td>
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</table>
In the next step, the LSPC model simulation (50 years) was extended back to 1947 using 5 years of warm up period. The model performance corresponding to long term simulation against the ANFIS model for the same period was compared, and found that the ANFIS model is relatively better than LSPC model (Table 8). In addition, we analyzed median observed and median simulated flow for each month and compared using the box plot diagram (Fig. 7). It is noteworthy to mention that the response of the two models varied significantly from season to season. The median observed and simulated flows from ANFIS model closely matched from January to August, and demonstrated significant difference for other months (September to December). However, the response of LSPC model is almost opposite leading to the significant difference from February to June, and close resemblance with the observed streamflow for other months (July to December). This indicates that ANFIS model can simulate streamflow resembling the actual observed flows for most of the year and LSPC can simulate better for low flow period. Because SST and SLP were directly implemented into a mathematical model (ANFIS), it was interesting for us to explore how this model would simulate streamflow
Moreover, we wanted to see how the conventional watershed model would simulate in a given condition, and also wanted to evaluate the best approach for streamflow simulation in the ENSO-affected region. The ANFIS model was compared with LSPC model, separately for La Niña and El Niño events, and found that ANFIS performed better than the LSPC model at different ENSO events due to the training of ANFIS model with long term data sets. The long term time series of ANFIS model and LSPC model simulation in historic ENSO events are shown in Fig. 8.

Since SST, SLP and trade wind index are the parameters related with basic ENSO phenomenon in the equatorial Pacific, we also found trade wind index as a sensitive input for the model. Since our objective was to run the model for 50 years to evaluate the performance of the model in different ENSO events, we had to exclude trade wind index as model inputs as these data were available for the last 34 years.

ANFIS demonstrated its competent performance over the LSPC model at daily scale as well, which implies that the model can be extended to lower temporal scales. However, the influence of climate variability in streamflow can be expected more distinct at monthly scales.

One of the reasons for better ANFIS model performance could be due to the use of long period of datasets starting since 1950 for model training for ANFIS model. Therefore, in order to make a realistic comparison (apples to apples) of ANFIS with LSPC, a shorter period of datasets was used. That is, the ANFIS model is trained, validated and tested using datasets from an exact period of LSPC model calibration and validation. ANFIS model performance in training and validation period was slightly better than the corresponding LSPC model calibration ($\text{NSE} = 0.85$ for ANFIS and $\text{NSE} = 0.83$ for LSPC) and validation ($\text{NSE} = 0.73$ for ANFIS and $\text{NSE} = 0.71$ for LSPC).

The model comparison between ANFIS and LSPC at different ENSO events and different scale suggest that ANFIS can simulate streamflow equally or better than the LSPC model, partly due to the explicit inclusion of the underlying ENSO phenomenon, but mainly due to the ANFIS model skill for a better simulation for the coarse rainfall data. It was essential to investigate that the SST/SLP has a contribution to partially improve the model simulation. To confirm this, we explored two methods; (1) first, we assessed the performance of ANFIS model including and excluding SST and SLP from its input vector, and found that ANFIS model performed better as we include SST and SLP (Table 8),

<table>
<thead>
<tr>
<th>Statistics</th>
<th>LSPC</th>
<th>ANFIS (with SST and SLP)</th>
<th>ANFIS (without SST and SLP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{NSE}$</td>
<td>0.68</td>
<td>0.79</td>
<td>0.74</td>
</tr>
<tr>
<td>$\text{MBE}$</td>
<td>1%</td>
<td>0.60%</td>
<td>1.27%</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.68</td>
<td>0.79</td>
<td>0.74</td>
</tr>
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</table>

Table 8
Performance of LSPC and ANFIS model during 50 years simulation at monthly time step.

Fig. 6. LSPC model validation and comparison with ANFIS model during LSPC model validation phase.

Fig. 7. Statistical analysis of monthly streamflow simulated using: ANFIS model (left panel) and LSPC model (right panel).
secondly, the winter season (JFM) simulation was tested using a simple MLR model as the ENSO signal was clear during this period. It was found that model improved in a winter season due to the direct application of SST and SLP in the model. Therefore, this conclusion will be true only for a period when ENSO has a better correlation with streamflow and may not be valid when ENSO does not have a clear signature with precipitation.

Lack of enough rain gauge station in a study watershed was clearly manifested in both model simulations. More importantly, we investigated the precipitation and corresponding observed streamflow, and found that some of the streamflow did not look like the proper match with the corresponding precipitation events indicating that rain gauge stations considered for streamflow simulation was not adequate to address the spatial variability of the rainfall. In this context, additional forcing of SST/SLP can surrogate the precipitation as the watershed was affected by ENSO.

7. Summary and conclusion

In this study, we developed a data-driven model (ANFIS) and a physically based watershed model (LSPC) in Chickasaw Creek watershed, located in Southern Alabama. Both models were developed for same period of datasets, and the model performance was investigated through comprehensive model comparison in numerous ways, including statistical analysis for various seasons and periods over 50 years of simulation period. ANFIS model was developed by directly executing the SST and SLP difference between Tahiti and Darwin. Performances of the two models were evaluated at different temporal scale. Also, the model performance was evaluated in various historic La Niña and El Niño events, encountered throughout the 50 years of simulation. Even though both models performed satisfactorily with reasonable accuracy, ANFIS inclined to perform slightly better. ANFIS models were developed with and without incorporating SST and SLP in its input vector in order to evaluate the role of SST and SLP for model development. Even though the improvement of the model using SST and SLP is not significant, improvement in a particular season when ENSO signal is clear, can be expected. ANFIS is capable to capture the low and high flows during winter La Niña and El Niño events suggesting the application of SST and SLP for the long term continuous streamflow simulation. ANFIS is equally competent to LSPC in any case whether SST and SLP are incorporated or not.

ANFIS model proved to be more appropriate than LSPC model for given watershed conditions especially for two reasons; (i) first, spatially distributed precipitation data were not available for physically based model, LSPC, (ii) second, SST and SLP were additional inputs for ANFIS, which could not be incorporated by LSPC model, (iii) third, numerous missing data and recording error in precipitation data could be surrogated by SST and SLP which were the additional inputs in ANFIS.

This research was particularly conducted for a single watershed with reasonable teleconnection of ENSO with local precipitation and temperature of the region. It would be appropriate to calibrate both models using fine resolution to coarse resolution precipitation data sets, particularly for a strongly ENSO-affected watershed with multiple model set up. Also, it would be appropriate to conduct the study in various watersheds for better generalization. In addition, separate ANFIS model for three different seasons would have been appropriate as ENSO correlation with precipitation/temperature is different in various seasons, and particularly opposite from August to October. Therefore, a single model developed for entire period

<table>
<thead>
<tr>
<th>Table 9</th>
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<tbody>
<tr>
<td>El Niño and La Niña years (Dec–April) from 1950 to 2003 (Sharma et al. (in press)).</td>
</tr>
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<td><img src="image" alt="" /></td>
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<table>
<thead>
<tr>
<th>Year</th>
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<th>Table 10</th>
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<tbody>
<tr>
<td>Model comparison for 25 ENSO events (monthly simulation).</td>
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<td><img src="image" alt="" /></td>
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</table>

<table>
<thead>
<tr>
<th>Statistics</th>
<th>LPSC-simulated</th>
<th>ANFIS-simulated</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSE for La Niña and El Niño events (since 1952)</td>
<td>0.67</td>
<td>0.83</td>
</tr>
<tr>
<td>MBE</td>
<td>−4.02%</td>
<td>3.10</td>
</tr>
<tr>
<td>R²</td>
<td>0.68</td>
<td>0.83</td>
</tr>
<tr>
<td>14 La Niña events (Table 9)</td>
<td>0.67</td>
<td>0.86</td>
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<tr>
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<td>5%</td>
<td>6%</td>
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<tr>
<td>R²</td>
<td>0.68</td>
<td>0.87</td>
</tr>
<tr>
<td>11 El Niño events (Table 9)</td>
<td>0.61</td>
<td>0.76</td>
</tr>
<tr>
<td>MBE</td>
<td>4.90%</td>
<td>−3.12%</td>
</tr>
<tr>
<td>R²</td>
<td>0.66</td>
<td>0.77</td>
</tr>
</tbody>
</table>

Fig. 8. Monthly streamflow simulation using LSPC and ANFIS models corresponding to historic La Niña and El Niño events (Table 9) since 1950. Dots and triangles represent ANFIS and LSPC simulation during La Niña and El Niño events.
cannot be expected to significantly improve the simulation by additional forcing of SST and SLP.

Future research can be conducted in ENSO affected watershed using ANFIS model, and incorporating trade wind index besides SST and SLP in its input vectors, as the trade wind index is also responsible for ENSO phenomenon. It is to be clearly mentioned that, the benefit of ANFIS model over the LSPC or any other physically based model, can be expected significant, especially for a watershed which is suffered from lack of adequate rain gauge stations and also affected by ENSO.

Even though this research does not conclude the supremacy of ANFIS model over the LSPC model, research concludes that ANFIS can be a better choice when rain gauge stations are limited. More importantly, ANFIS provides an opportunity to consider additional inclusions of long term SST and SLP in the equatorial Pacific in order to explicitly utilize the ENSO pattern for hydrologic modeling. This might be helpful as and when spatially distributed precipitation datasets are not available and the watershed is affected by ENSO.

References


