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Multiscale hydrological drought analysis: Role of climate, catchment and morphological variables and associated thresholds

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ABSTRACT

Identification of thresholds associated with key climate, catchment and morphological variables for hydrological droughts can further improve our understanding of evolution and propagation of droughts in a complex water resource system. These thresholds are associated with complex interaction between climate and catchment variables and they are often connected through hierarchical as well as non-linear relationships. The advantage of selecting a multi-factor predictor domain can detect multiple thresholds that may not be observed by analyses limited to single predictors. In the present study, we developed a conceptual modeling framework by integrating a hydrological model developed based on the Soil and Water Assessment Tool (SWAT) and statistical models to quantify the potential influence of climate, catchment, and morphological variables and their thresholds on hydrological drought duration and severity for the watersheds located in Savannah River Basin (SRB). The concept of standardized runoff index (SRI) was used to derive the multiscale hydrological drought time series (i.e., SRI 1, SRI 6, and SRI 12) to investigate short term, medium term, and long term drought events based on their duration and severity. It was observed that the linear models developed based on the climate variables may not be capable for predicting the duration of multiscale hydrological droughts, whereas, the performance of statistical models can be significantly improved by the addition of catchment and morphological variables. In addition, among the morphological variables stream order seems to have a significant control over short, medium and long term drought duration across the study area. In the second phase of our analysis, we employed classification and regression tree (CART) algorithm for quantifying the thresholds associated with climate, catchment, and morphological variables that have potential influence on the hydrological drought. The result indicates that the variables and its associated threshold vary for short, medium, and long term drought. The proposed modeling framework can be extended for ungauged basins to improve the drought management.

1. Introduction

A prolonged drought has a significant impact on the socio-economic, environmental and ecological systems that affects millions of people around the world each year (Domeisen, 1995; Carlowicz, 1996; Wilhite, 2000; Mishra and Singh, 2010; Dai, 2011; Konapala and Mishra, 2020). Drought has direct or indirect impact on multiple sectors (Wilhite et al., 2007), such as economic loss (Wilhite, 2000), mortality and conflicts (García-Herrera et al., 2010; Hsiang et al., 2013), ecology (Choat et al., 2012), agriculture (Mishra et al., 2015) and water resources planning and management (Rajsekhar et al., 2015; Mishra and Singh, 2011). Drought affects water quantity (Lund and Reed, 1995) and quality (Van Vliet and Zwolsman, 2008) of surface and groundwater systems (Mishra and Singh, 2010). Due to the complex interaction between climate, catchment, and morphological processes, the quantification of drought events initiation and termination are often challenging (Van Loon and Laaha, 2015; Veettil and Mishra, 2018; Konapala and Mishra, 2017, 2020).

The drought events in the future are anticipated to increase in the continental United States due to the climate change (Sheffield et al., 2012). For instance, in 2002 more than 50% of the North American continent witnessed moderate to severe drought (Lawrimore and Stephens, 2003; Cook et al., 2007). The drought severity in the last decades increased not only in the west, but also in the southeastern part of the USA (Clark et al., 2016). For example, the southeast United States experienced significant drought during 1965 to 1971, 1980 to 1982, 1985 to 1988, 1998 to 2002 (Weaver, 2005) and 2006 to 2009 (Veettil and Mishra, 2016).

A number of drought indices are used for quantifying different types of drought (Mishra and Singh, 2010), such as Palmer Drought Severity

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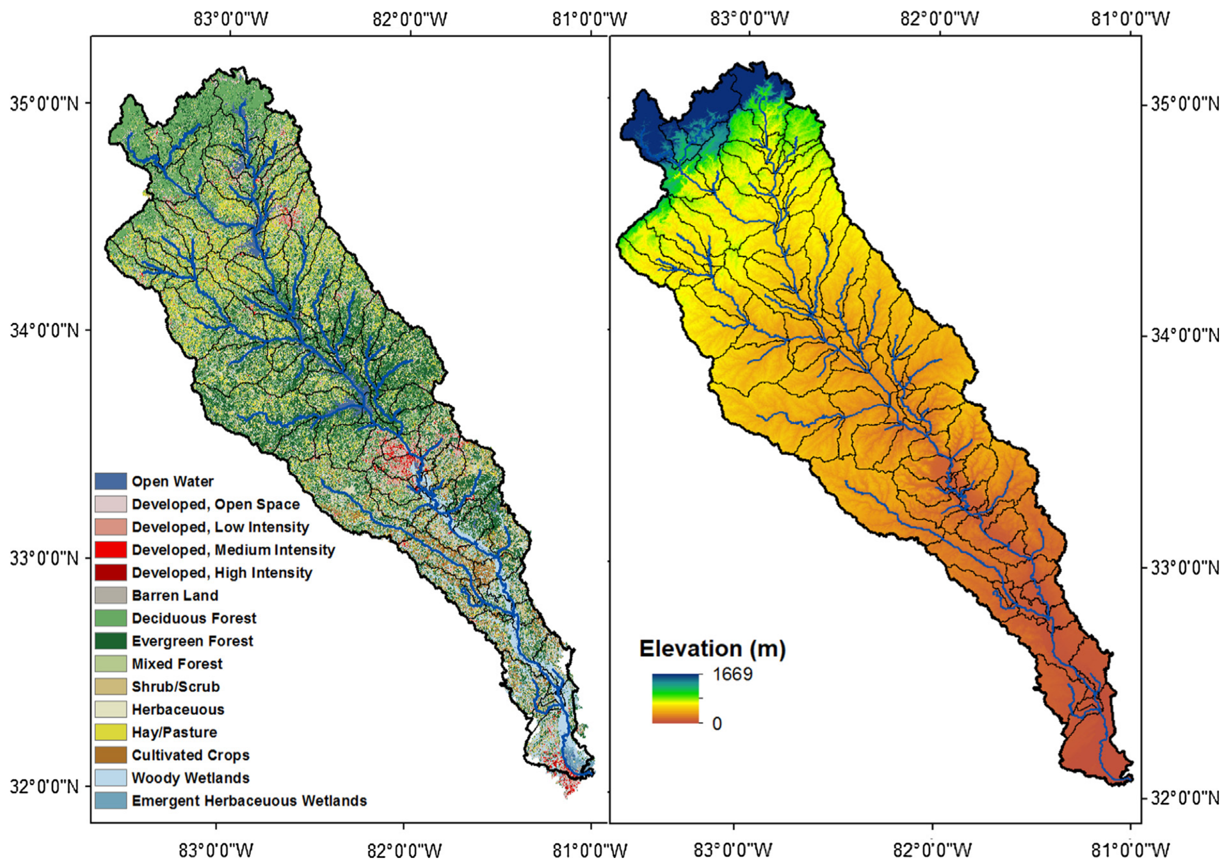

Fig. 1. (a) Land use and land cover map, and (b) topography of the Savannah River Basin.

Index (PDSI; Palmer, 1965), Crop Moisture Index (CMI; Palmer, 1968), and standardized precipitation index (SPI; McKee et al., 1993). In this study, we applied the concept of Standardized Runoff Index (SRI, Shukla and Wood, 2008) for quantifying the hydrological drought for the watersheds located in Savannah River Basin. Hydrological drought has direct impact on multiple stakeholders such as irrigation, electricity generation, and recreation purpose within a river basin (Van Vliet et al., 2012; Mishra and Singh, 2010). Therefore, better understanding of hydrological drought can be more meaningful for surface and groundwater water resources management.

Hydrological drought occurs when the surface flow (river flow) and lakes or reservoirs levels decline below long term mean (Mishra and Singh, 2010; Van Loon, 2015). It can be also termed as streamflow drought (Clausen and Pearson, 1995). Hydrological drought assessment at a catchment scale is often difficult due to limited observed data sets. Moreover, from a water resources management point of view, the duration and severity analysis of a hydrological drought is essential. The information on duration of hydrological drought is predominantly crucial for lives in an aquatic ecosystem (Humphries and Baldwin, 2003), and quantifying the drought severity is more important for abstraction of water from a stream for different purposes (e.g. hydropower production, mining, and domestic use). Similar to the other categories of drought, the anomalies in atmospheric processes initiates the hydrologic drought.

The propagation of hydrological drought is not only related to the climate characteristics but it is also influenced by the catchment properties (Peters et al., 2006; Tallaksen et al., 2009; Mishra and Singh, 2010; Van Loon 2015; Konapala and Mishra, 2020; Wanders et al., 2010) and morphology of stream network (Bond et al., 2008). For instance, a decrease in soil moisture storage in a catchment causes depletion in the amount of water contributed to the aquifer system which further causes gradual drying of ground water discharge (base flow) and tapering of stream flow (Huntington and Niswonger, 2012) leading to hydrological drought. Additional catchment characteristics, such as land use type (e.g. forest area, grass land, and agriculture), catchment elevation, and soil type also influence initiation of hydrological drought. There are few studies that investigated the combined influence of climate and catchment variables on hydrological droughts (e.g., Van Loon and Laaha, 2015; Konapala and Mishra, 2020).

Although the definition of hydrological drought is straightforward, the challenge remains to understand the process that triggers these drought events (Van Loon, 2015; Konapala and Mishra, 2020), therefore it is important to identify key variables and associated thresholds that controls these hydrological droughts. The quantification of thresholds can result from complex interaction between climate and catchment variables and they are often connected through hierarchical as well as non-linear relationships. The identification of thresholds from a set of multi-factor predictor domains can detect multiple thresholds that may not be observed by analyses limited to single predictors. The specific objectives of this study are: (a) to investigate the influence of (either individually or combined) climate, catchment and morphological variables responsible for triggering hydrological drought in Savannah River Basin, and (b) to identify the threshold limits for the climate, catchment and morphological variables that triggers the hydrological drought using the concept of decision tree. The identification of threshold limit can provide useful information for decision makers to identify appropriate variables that can trigger the short, medium and long term hydrological drought.

2. Study area and data

The Savannah River Basin (SRB) is located in Southeastern USA with a total drainage area of 27171 km^2, and it is partly located in the state of South Carolina (11875 km^2), Georgia (14965 km^2) and North

Carolina (331 km^2) (SCDHEC, 2010; Veettil and Mishra, 2016, 2018). The major land use and land cover of the basin includes forest (60%), agriculture (14%), settlement (10%) and open water (4%). The annual precipitation over the basin varies from 1000 mm to 2050 mm (SCDHEC, 2010). The rainfall is evenly distributed throughout the year, but a dry weather occurs from midsummer to fall. The mean annual temperature of the basin is 18 °C (SCDHEC, 2010). The climate of SRB is characterized by mild winters and hot summers in the lower portions and cold winters and mild summers in the upper section of the SRB (Wachob, 2010). The SRB and its major land use classes are shown in Fig. 1(a) and the elevation of each catchment of the SRB is illustrated in Fig. 1(b).

2.1. Data

The datasets were collected from multiple sources to develop a SWAT model for the study area. These data sets includes: (a) the digital elevation model (DEM) was obtained from National Elevation data set (NED, USGS) at a resolution of 30 m. The DEM was used for delineating the study area and to estimate the topographic features, (b) the land use data was obtained from National Land Cover Dataset (NLCD) for the period 2011, (c) the soil data was downloaded from SSURGO database of United State Department of Agriculture (USDA), (d) the meteorological (precipitation and temperature) data for the year 1990 to 2013 were collected from National Climatic Data Centre (NCDC). The weather input file must contain data for entire period of simulation in a daily time scale. We performed quality control on available weather data, and the missing values are filled up based on the interpolation from neighboring stations as well as based on SWAT weather generator (Arnold et al., 2012). (e) The stream flow data for the year 1990 to 2013 were obtained from and United States Geological Survey (USGS). The reservoir outflow data for the year 1990–2013 were collected from the Savannah District Water Management (US Army Corps of Engineers) and incorporated in the SWAT model development. Overall seven climate variables are used in this analysis, which includes mean annual precipitation, evapotranspiration, number of wet and dry spells, and mean precipitation during spring, summer and fall seasons. Seventeen variables are selected to represent catchment characteristics, and few examples are catchment area, land use classes, base flow index (BFI), and soil types. The morphological characteristics are represented by eight variables, which include stream order, drainage density, relief, relief ratio, form factor, circularity ratio, elongation ratio and length of overland flow.

3. Methodology

The modeling framework developed for quantifying the potential influence of climate, catchment, and morphological variables and associated thresholds on the hydrological drought duration (severity) for the watersheds of SRB is shown in Fig. 2. The following sections elucidate the specific components incorporated in the modeling framework.

3.1. Hydrologic model

The Soil and Water Assessment Tool (SWAT) developed by United States Department of Agriculture (USDA) (Arnold et al., 1995; Neitsch et al., 2004) was employed for simulating the hydrological fluxes of SRB. The SWAT is a process based, semi-distributed basin scale model (Arnold et al., 1998; Santhi et al., 2001) and it operates based on the daily time series of meteorological input. The SWAT model can be used for simulating evapotranspiration, plant growth, infiltration, percolation, runoff, nutrient loads, and erosion (Neitsch et al., 2004; Faramarzi et al., 2009) from a small catchment scale to a continental scale (Chu et al., 2004; Giri et al., 2014). The SWAT model has been tested in different sectors (e.g., agricultural water management, water scarcity,

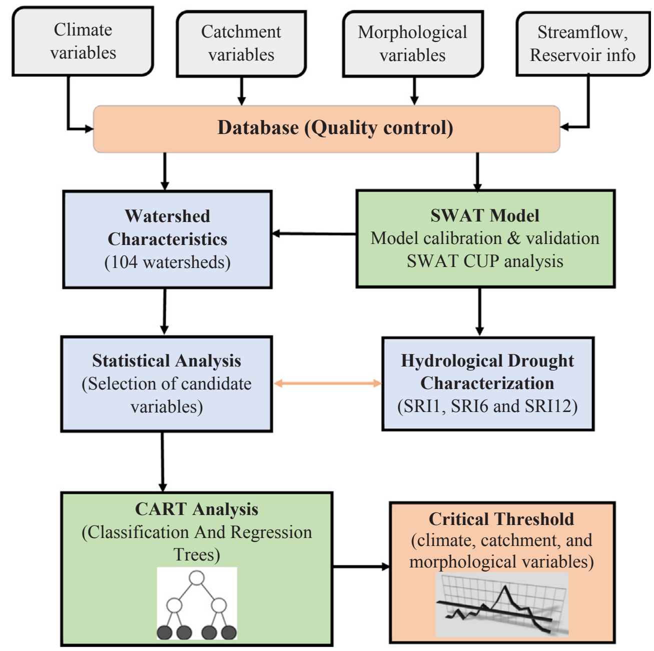

Fig. 2. The modeling framework developed for quantifying the potential influence of climate, catchment, and morphological variables and associated thresholds on the hydrological drought.

and water quality management) and discussed extensively in the literatures (Gassman et al., 2007). More recently SWAT model has been applied for improving drought management (Wu and Johnston, 2007; Zhang et al., 2007; Wang et al., 2011; Kamali et al., 2015; Bucak et al., 2017).

Digital Elevation Models (DEMs) are the basic input data for developing the SWAT model. The delineation of the watershed is performed based on the topographic data stored in the DEM pixel cells (Fig. 1b). Here, we used DEM prepared by National Elevation Dataset (NED), which has a resolution of 30 m. In the SWAT model, the delineated river basin is divided into sub-basins and each sub-basin is further divided into Hydrologic Response Units (HRUs). The hydrological response units are created based on unique land use, soil and slope data provided to the model. Overall, 1408 HRUs are created over 104 sub-basins located in SRB. Surface runoff is estimated by Soil Conservation Service-Curve Number (SCS-CN) equation based on daily precipitation data and soil hydrologic group, land use and land cover characteristics and antecedent soil moisture. A detailed description of the SWAT model is provided by Neitsch et al. (2004). In the present study, we used ArcSWAT 2012 with ArcGIS interface (ESRI-version 10.2.2).

The SUFI2 optimization algorithm in the Soil and Water Assessment Tool Calibration and Uncertainty Analysis Program (SWAT-CUP) developed by Abbaspour (2005) was utilized for calibrating the SWAT model parameters. The parameter sensitivity analysis is performed based on the p-value and *t*-test, which is an inbuilt option in the SWAT CUP (Abbaspour et al., 2007). SUFI2 algorithm can narrow down the range of uncertainty by identifying a range of parameters that reduce overall uncertainty in the developed model and model output (i.e. streamflow) is quantified by 95% prediction uncertainty (95PPU) calculated at 2.5% and 97.5%. The goodness of fit criteria utilized to analyze the SWAT model performance are coefficient of determination (R^2), Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliff, 1970), R- and P-factor. The overall time period used for evaluating the SWAT model performance is 1990–2013. The first three years (i.e. 1990–1992) were used as warm-up period to initialize important model process and related variables, and subsequently this time period is excluded from the analysis. Finally, the model was simulated and evaluated against the observed USGS stream flow data available from 1993 to 2013. We divided the stream flow dataset in to two periods for calibration (1993–2005) and for validation (2006–2013). The model performance and calibrated parameters are explained in Section 4.1.

3.2. Standardized runoff index (SRI)

The SRI (Shukla and Wood, 2008) is based on the concept of standardized precipitation index (SPI; McKee et al., 1993). In this study, SRI was used to quantifying the hydrological drought characteristics (e.g. duration and severity) for 104 watersheds located in Savannah River Basin. The following steps were used for deriving the SRI: (a) The monthly time series of stream flow data was extracted for 104 watersheds located in SRB using the well calibrated SWAT model; (b) These long term streamflow record is fitted to a suitable probability distribution. In our study, we identified Gamma distribution as the best model based on the Chi-Square Goodness of Fit Test. The Gamma distribution can be a reasonable descriptor of the monthly flow series compared to other distributions (Sharma and Panu, 2014); (c) Once the probability density function is determined, the cumulative probability of the streamflow time series at different time scale is computed; and (d) the inverse normal Gaussian function, with mean zero and variance one, is then applied to the cumulative probability distribution function, which results in the SRI (Table 1). In this study, we selected a threshold of SRI < -1 to identify moderate to higher drought events for our analysis. Based on this concept, we calculated the drought duration and severity of hydrological drought for each 104 watersheds using theory of runs (Mishra and Singh, 2010). Subsequently, the SRI analysis is performed for three time scales to represent short term drought (accumulation period of 1 month, SRI 1); medium term drought (accumulation period of 6 months, SRI 6); and long term drought (accumulation period of 12 months, SRI 12). The average drought duration and severity are calculated with respect to the total number of drought events occurred for each watersheds of SRB using a time period 1993 to 2013.

3.3. Analysis of climate, catchment and morphological variables

We investigated the potential influence of climate, catchment and morphological variables (Table 2) on hydrological drought duration and severity by using linear and non-linear statistical analysis. In the first part of our investigation, we applied bivariate correlation analysis for exploring the strength of linear relationship between the drought characteristics and individual climate, catchment, and morphological variables. Subsequently, we applied multi-linear regression analysis and backward stepwise selection method to a group of variables and the non-linear CART (Classification and Regression Tree) approach for quantifying the threshold of each of the selected variables for predicting the hydrological drought duration and severity. An overview of these methodologies are discussed in the following section:

3.3.1. Variables selection

In the first phase of our investigation, the bivariate correlation analysis was applied to explore the strength of relationship between the drought characteristics and individual climate, catchment, and morphological variables. It is possible that, the collinearity may exist between different variables used in the study. Therefore, we generated the correlation matrix of pairwise combinations of all variables based on the Pearson correlation coefficient. The correlation matrix allowed us to identify the interdependence among the climate, catchment, and morphological variables. Initially, the linear regression analysis was performed based on individual climate, catchment and morphological variables for investigating their role in drought severity and duration. Then we applied the backward stepwise selection method to select a subset of variables from climate, catchment and morphological variable space. These selected variables can be considered as key variables for influencing the hydrological drought in the SRB. Subsequently, the best model from backward stepwise selection method is selected by using Akaike Information Criterion (AIC) (Akaike, 1974).

Table 1
Classification of drought category for the SRI.

SRI Values	Drought Category
0 to −0.99	Mild drought
−1.00 to −1.49	Moderate drought
−1.50 to −1.99	Severe drought
< −2.00	Extreme drought

Table 2
List of Climate, Catchment, and Morphological variables used in this study.

Name	Climate variable definition	Unit
A.PCP	Annual average precipitation	mm
A.ET	Annual average evapotranspiration	mm
Wet Spell	Number of months with precipitation more than average monthly precipitation	–
Dry Spell	Number of months with precipitation less than average monthly precipitation	–
PCP.SPN	Average precipitation during spring season	mm
PCP.SUM	Average precipitation during summer season	mm
PCP.FAL	Average precipitation during fall season	mm
Name	**Catchment variable definition**	**Unit**
Area	Area of the catchment	km^2
Slop	Slope of catchment	%
Length	Longest flow path of stream in a catchment	m
Width	Width of stream in a catchment	m
Depth	Depth of stream in a catchment	m
Elev	Elevation of the catchment	m
ElevMin	Min elevation in the catchment	m
ElevMax	Max elevation in the catchment	m
O. Water	Open water area in a catchment	–
D. Area	Developed area in a catchment	–
B. Land	Barren land in a catchment	–
F. Land	Forestland in a catchment	–
S. Land	Shrub land in a catchment	–
P. Land	Percentage of pastureland in a catchment	–
loamy	Percentage of loamy soil in a catchment	%
clayey	Percentage of clayey soil in a catchment	%
Sandy	Percentage of sandy soil in a catchment	%
Name	**Morphological variable definition**	**Unit**
Drainage Density (DD)	Ratio of stream length to Area of the basin	–
Stream order (S.Order)	Hierarchical ranking of streams	–
Relief (R)	Difference between maximum and minimum elevation	m
Relief ratio (RR)	Ratio of relief of a catchment to basin length	–
Form factor (FF)	It is the ratio of area of a catchment to squire of the basin length.	–
Circularity ratio (CR)	Calculated as 4*Pi * A/P^2. Where Pi = 3.14 and P is the square of the perimeter.	–
Elongation ratio (ER)	ER = 2/Basin length	–
Length of overland land flow (LF)	LF = 1/D * 2	–

3.3.2. Classification and regression trees (CART)

The CART models were developed to identify the threshold associated between climate, catchment and morphological variables and hydrological drought. We developed classification and regression tree using a recursive partitioning algorithm, which classifies the space defined by the input variables (e.g. climate, catchment, and morphological variables) based on the output variables (e.g. drought characteristics). The CART is an effective representation of stepwise decision making process of a complex system (Solomatine, 2002) by stratifying the predictor space to a number of simple regions, based on the output variable (Breiman et al., 1984; James et al., 2013; Deshmukh and Singh, 2016). In addition, the method is simple to use and easy to interpret and it can be considered as one of the most appropriate approach among supervised learning techniques (James et al., 2013). Overall, the set of splitting rules divide the predictor space into various classes is represented as a tree. Therefore, these types of approaches are known as decision (or classification) tree methods. In this tree like structure, the nodes contain the conditions or threshold of the variables that control the hydrological drought across the watersheds. Whereas, the leaves represent the magnitude of hydrological drought duration and severity.

The following steps are used to develop the decision tree model for quantifying the thresholds associated with climate, catchment and morphological variables: (i) the response and predictor variables are first selected for individual watersheds located in SRB, where the response variables are drought characteristics (i.e. drought duration and severity) and predictor variables are climate, catchment, and morphological variables of particular watersheds; (ii) Divide the predictor space that is the set of predictor variables $X_1, X_2, \ldots, X_p$ into J discrete and non-intersecting regions, such as $R_1, R_2, \ldots, R_J$; and (iii) for every variables that fall into the region R_j, the tree makes the same prediction, which is the mean of the drought characteristic values in the region R_j. The purpose of dividing predictor space into different regions (R_1, R_2, … , R_J) is to minimize the residual sum of squares (RSS), given by

$$RSS_{Min} = \sum_{j=1}^{J} \sum_{i \in R_j} (y_i - \hat{y}_{R_j})^2 \tag{1}$$

where, $\hat{y}_{R_j}$ is the mean response of the response variable (drought characteristics) within the j^{th} region. Generally, by considering every possible partition of predictor feature space into distinct regions is computationally challenging. Therefore, decision tree algorithm utilize recursive binary splitting, which is based on a top-down approach by successively splitting the predictor space represented by two new branches further down on the tree. In order to perform the recursive binary splitting, we first selected the predictor Xj and the threshold $\boldsymbol{s}$ (Eqs. (2) and (3)), so that by splitting the predictor space can lead to maximum reduction in RSS, which is given by Eq. (4).

$$R_1(j, s) = \{X|X_j < s\} \tag{2}$$

$$R_2(j, s) = \{X|X_j \geq s\} \tag{3}$$

$$\sum_{i:x_i \in R_1(j,s)} (y_i - \hat{y}_{R1}) + \sum_{i:x_i \in R_2(j,s)} (y_i - \hat{y}_{R2}) \tag{4}$$

The final selection of predictor variable and associated threshold is based on the lowest RSS for the resulting tree. The output of the tree divides data into a number of classes (or series of nodes) and each node represents the ranges of hydrological drought duration/severity in the form of a boxplot. The final tree provides the threshold and significance (p-value) value of each variable that has a potential influence on the hydrological drought in the SRB.

4. Results

4.1. SWAT model performance evaluation

The SUFI2 algorithm was applied for performing the parameterization and sensitivity analysis of SWAT model. The SWAT model is calibrated and validated at the 6 gauging stations located in the upper, central, and lower portion of the SRB. Overall, 17 parameters were calibrated for simulating the stream flow and most sensitive parameters are identified based on p-value and *t*-test provided in the global sensitivity analysis (i.e. inbuilt option in the SWAT CUP). A list of 10 most sensitive parameters are provided in Table 3. The goodness of fit statistics (R^2, NSE, P-factor and R-factor) between SWAT based flow and observed flow (for four hydrologic stations located in the SRB) is provided in the Table 4. The time series plot between SWAT simulated flow and observed flow at USGS stream gaging stations (02192000 and 021985000) are shown in Fig. 3. A detailed explanation on model parameterization and sensitivity analysis is provided in Veettil and Mishra (2016).

Table 3
Most sensitive parameters used for the SWAT model calibration and validation.

Sensitive Parameters	Explanation	Calibrated range
r_CN2.mgt	Curve number	−0.2 to 0.3
r_SOL_AWC. Sol	Available water capacity of the soil layer	−0.2 to 2
v_ALPHA_BF.gw	Baseflow recession constant	0.4 to 0.9
v_GW_DELAY.gw	Groundwater delay time (days)	30 to 450
r_GW_REVAP.gw	Groundwater revap. coefficient	0.02 to 0.2
r_HRU_SLP.hru	Average slope steepness (m/m)	−0.5 to 1
r_SLSUBBSN.hru	Average slope length (m)	−0.5 to 1
r_EPCO.bsn	Plant uptake compensation factor	0 to 0.7
r_ESCO.bsn	Soil evaporation compensation factor	0 to 0.4
v_CH_N2.rte	Manning's n value for the main channel	0.01 to 0.4

4.2. Overview of multiscale hydrological droughts in the Savannah River Basin

In the present study, the SWAT model was used to generate streamflow and further SRI time series for 104 watersheds located in the SRB. Subsequently, the multiscale hydrological drought time series were derived based on SRI 1, SRI 6, and SRI 12 based on the streamflow accumulation periods of 1-month, 6-months, and 12-months respectively. The boxplot and spatial distribution of average drought duration and severity of short, medium and long term droughts based on SRI 1, SRI 6, and SRI 12 for the watersheds located in the SRB are shown in Fig. 4. The average duration of short term drought based on the SRI 1 varies between 3 and 23 months, for medium term drought based on the SRI 6 it varies between 14 and 54 months, and for the long term drought the average duration varies between 28 and 89 months derived based on SRI 12. It can be clearly observed that the average duration of drought event increases as the temporal scale of SRI increased. This analysis suggests that the SRI 1, SRI 6, and SRI 12 can be used to classify drought duration in to short, medium and long term events.

It was observed that the distribution of average drought duration and severity varies among watersheds for short, medium, and long term drought. In the case of average drought severity, short term drought showed a median of 10 (Fig. 4a). The average drought severity for short term drought is relatively less in the upper watersheds of SRB. Whereas, the maximum severity was observed in the central watershed located farther from the mainstream network. The boxplot of average drought duration for SRI 1 showed a median of 10 months in the SRB. Similar to the drought severity, the average duration of short term drought is comparatively less in the upper part of the SRB, where the duration of drought events varies from 2 to 9 months (Fig. 4a). However, for the watersheds located in the lower part of the basin exhibited drought duration up to 23 months for SRI 1 drought. It was also observed that the short term drought duration and its severity is comparatively less in the most of the watersheds located near to the main stream network. On the other hand, the watersheds located farther from the mainstream network exhibited higher values of short term drought duration and severity.

The boxplot of average drought severity for SRI 6 is shown in Fig. 4a, which indicates a median value of 32 for SRB (Fig. 4a). The spatial distribution of average drought duration for SRI 6 drought also showed a similar pattern of average drought severity. Similar to the short term drought, the watersheds located in the upper part of the SRB exhibits lower values of medium term drought duration and severity. Whereas, drought duration and severity increases towards lower parts

Table 4
Goodness of fit statistics between SWAT simulated and USGS observed streamflow for selected stations.

USGS flow station	Latitude/Longitude	Station ID	Calibration period				Validation period			
			R^2	NSE	R- factor	P- factor	R^2	NSE	R- factor	P- factor
Broad River near Bell	33°58′27″/82°46′12″	02192000	0.88	0.87	0.89	0.81	0.81	0.77	0.57	0.71
Savannah River near Clyo	32°31′41″/81°16′08″	02198500	0.85	0.76	0.89	0.82	0.64	0.58	0.58	0.51
Savannah River at Augusta	33°22′25″/81°56′35″	02197000	0.54	0.45	0.86	0.66	0.55	0.42	0.89	0.53
Savannah River at Burtons Ferry Br Nr Millhaven	32°56′20″/81°30′10″	02197500	0.62	0.62	0.84	0.76	0.55	0.38	0.76	0.63

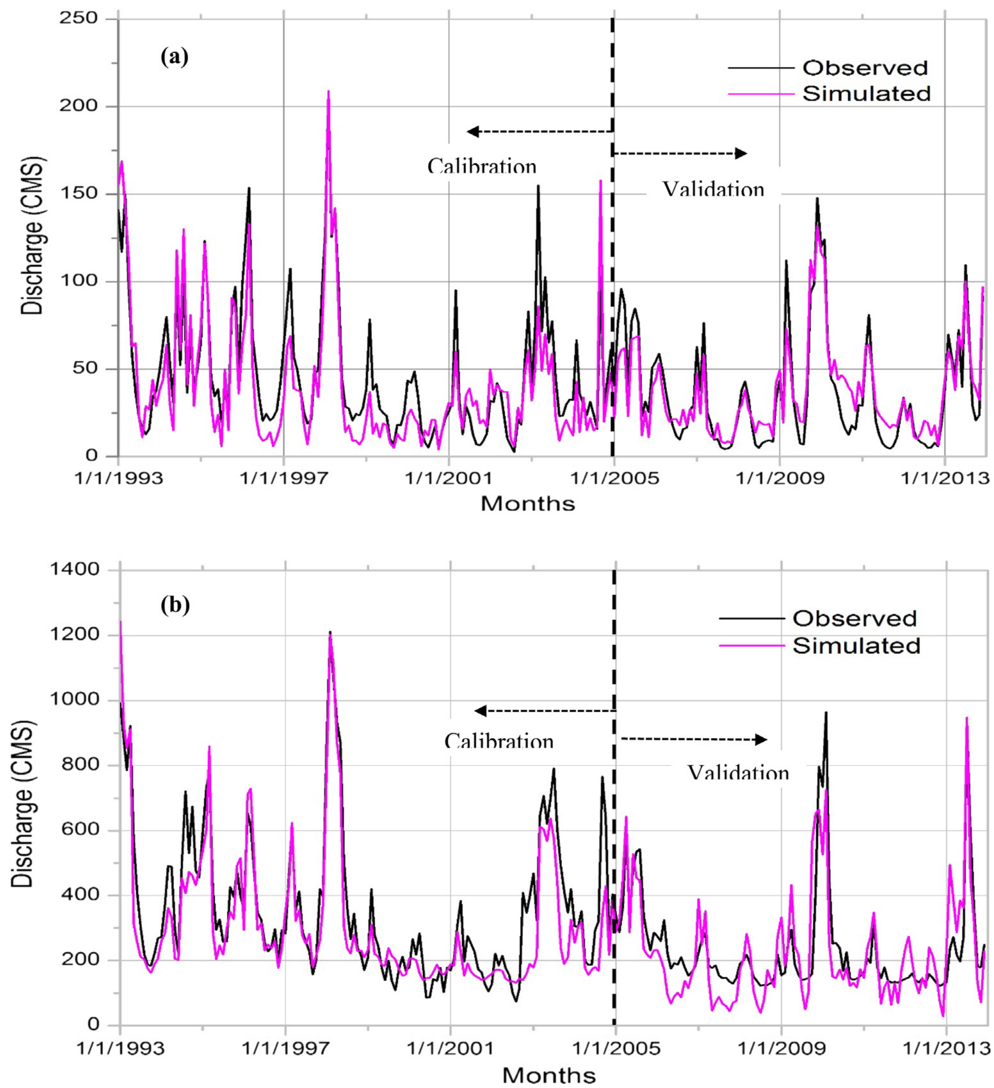

Fig. 3. Time series plot between modeled (SWAT) and observed (USGS) stream flow at gauging stations (a) 02192000 and (b) 021985000 at monthly time scale (Veettil and Mishra, 2016).

of SRB. Most of the watersheds located in the central part of the basin witness higher duration of droughts that varies between 34 and 54 months, and severity values between 35 and 47. It was also observed that the percentage of area affected by medium term drought across the watersheds of SRB was comparatively higher than short term and long term drought. In the case of long term droughts, the boxplot of average drought duration and severity showed a median of 37 months and 42 respectively. The spatial distribution of average drought duration for SRI 12 varies between 28 and 89 months over the SRB, whereas the severity ranges from 24 to 97. It was observed that the number of watersheds with higher drought duration is less in the SRB. Unlike the medium term drought, higher values of long term drought were distributed over the watersheds located in Georgia State. Overall, the spatial pattern of short, medium, and long term drought duration and severity obtained from different SRI time series varies within the SRB.

Fig. 5 illustrates the correlation between average hydrological drought duration and severity derived from these three SRI time series for watersheds located in SRB. It was observed that both drought characteristics are correlated to each other, however the correlation strength changes as the timescale of SRI time series increases. For example, stronger linear correlation was observed for SRI 1 (correlation coefficient = 0.91), and it is reduced for SRI 6 (correlation coefficient = 0.82), which further dramatically reduced for SRI 12. The scattered plot for SRI 12 appeared in two distinct clusters located in

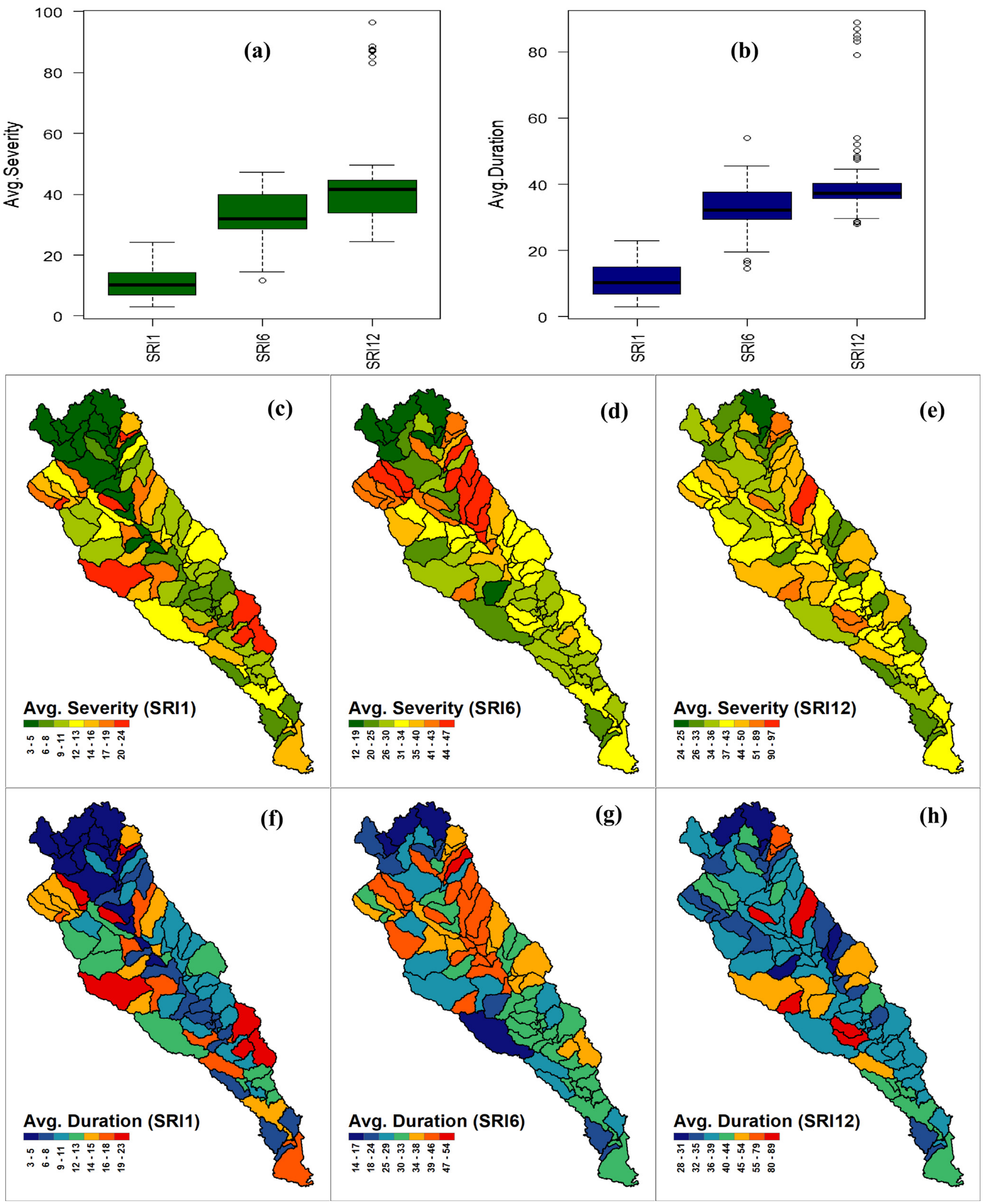

Fig. 4. Boxplot of (a) average severity and (b) average duration of short term droughts based on SRI 1, medium term drought based on SRI 6, and long term drought based on SRI 12. Spatial distribution of average severity for (c) SRI 1, (d) SRI 6, and (e) SRI 12, and spatial distribution of average duration for (f) SRI 1, (g) SRI 6, and (h) SRI 12 for the watersheds located in Savannah River Basin.

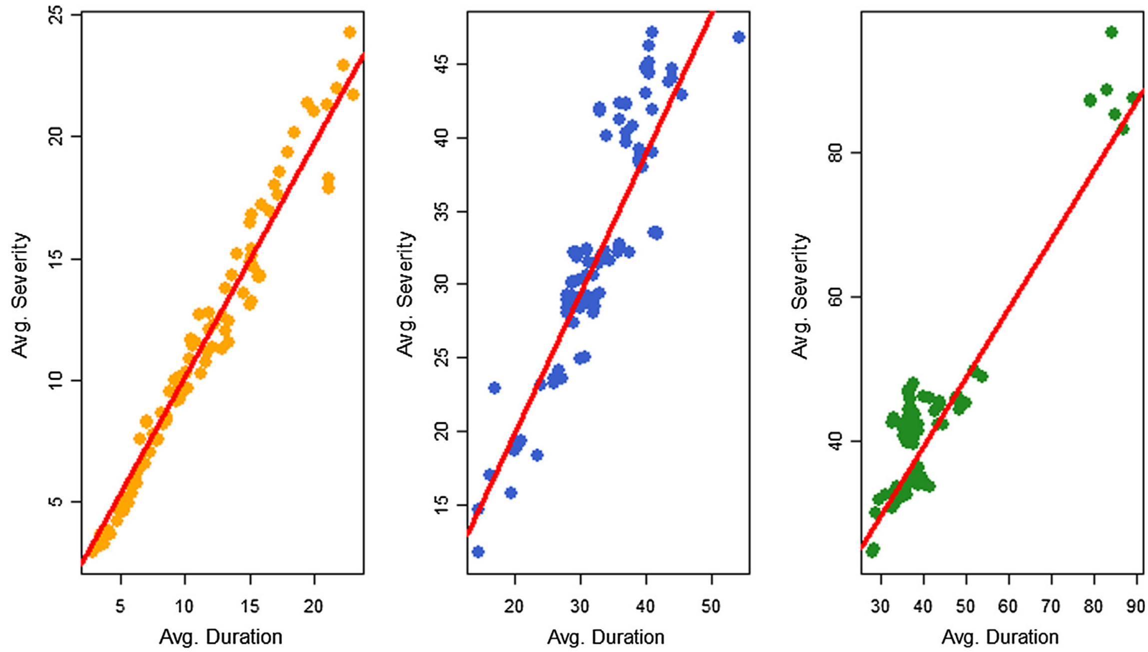

Fig. 5. The scattered plot between hydrological drought average duration (Avg. Duration) and severity (Avg. Severity) for (a) SRI 1, (b) SRI 6 and (c) SRI 12.

lower and higher ends. It was observed that the correlation strength between drought severity and duration share a linear relationship for low SRI time scales (e.g., SRI 1 and SRI 6). However, at higher time scales (e.g., SRI 12), the correlation strength likely to change from linear to non-linear relationship. This non-linear relationship may be attributed to the complex non-linear interaction between climate and catchment characteristics including potential role of base flow depending upon the surface water and groundwater interactions. This highlights the potential influence of climate, catchment, and morphological variables can be different for multiscale hydrological drought duration and severity.

4.3. Spatial pattern of key climate, catchment and morphological variables

The difference in spatial patterns of short, medium, and long term hydrological droughts are likely to be associated with the difference in spatial distribution of climate, catchment, and morphological variables of a river basin. Therefore, it is important to investigate the spatial distribution of key variables, which are strongly correlated with short, medium, and long term drought across the watersheds of SRB. The boxplot of important climate, catchment, and morphological variables across the SRB is illustrated in Fig. 6. In the case of climate variable, the magnitude of mean annual precipitation varies between 1045 mm and 2293 mm with a median of 1200 mm. The spatial pattern of mean annual precipitation during the period of 1993–2013 over the SRB is provided in Fig. 7a. It was observed that the higher magnitude of annual precipitation is distributed over the upper watersheds of the SRB. The spatial distribution of rainfall plays an important role on hydrological drought (Tran et al., 2015; Beyene et al., 2014; Van Lanen et al., 2013), as the deficit in rainfall triggers meteorological drought and further it leads to hydrological drought (Mishra and Singh, 2010). The higher magnitude of rainfall can be a possible reason for the lower duration of hydrological drought for the watersheds located in the upper part of SRB. The boxplot of average seasonal precipitation during the spring, summer, and fall season shows a median of 400 mm, 319 mm, and 481 mm respectively. The spatial pattern of mean precipitation during spring (PCP.SPN), summer (PCP.SUM), and fall (PCP.FAL) season for the SRB is shown in Fig. 7. The PCP.SPN varies between 308 mm and 750 mm across the watersheds whereas; the PCP.FAL varies between from 300 mm to 975 mm, and the PCP.SUM varies between 280 mm and 595 mm. It was observed that, during summer season the precipitation is comparatively higher across the watersheds located in lower SRB.

The boxplot of important catchment variables such as base flow index (BFI), pastureland, wetland, forestland, catchment area, and elevation is illustrated in Fig. 6b and c. The spatial distribution of the catchment variable BFI varies between 0.15 and 0.41 for the watersheds located in the SRB (Fig. 7e). The BFI is a measure of slow and continuous contribution of ground water to the streamflow (Smakhtin, 2001) and in most of the dry season, the entire stream flow is contributed by the base flow. The BFI has a strong role in controlling the storage capacity and response time of a catchment and it is also a good indicator of the geological characteristics of a catchment (Bloomfield et al., 2009; Hidsal et al., 2004; Smakhtin, 2001). Here, the BFI is derived based on ‘automated base flow separation and recession analysis techniques” developed by Arnold et al. (1995), which utilize a digital filter based automated base flow separation technique, which is capable to produce the results similar to the graphical separation technique. The boxplot of catchment variables related to the land use classes such as pastureland, wetland, and forestland are shown in Fig. 6b. The range of these catchment variables are expressed as the ratio between the areas of land use class in a catchment to the total area of the catchment. The pastureland, wetland, forestland ranges from 0 to 0.35, 0 to 0.62, and 0.02 to 0.92 respectively across the watersheds of SRB. The land use plays an important role in controlling the hydrological drought in a watershed. For instance, the pastureland increases the amount of evapotranspiration and reduce the water yield capacity (Zhang et al., 2016), therefore a larger area of pastureland may lead the catchment to hydrological drought. Fig. 6d illustrates the boxplot of morphological variables such as form factor (FF), circulatory ratio (CR) and elongation ratio. The morphological variable, stream order (S.Order) varies between one and four for the watersheds located in the SRB (Fig. 7f) and it was also observed that the watersheds located close to the main river network exhibit higher values of S.Order (Hakala and Hartman, 2004).

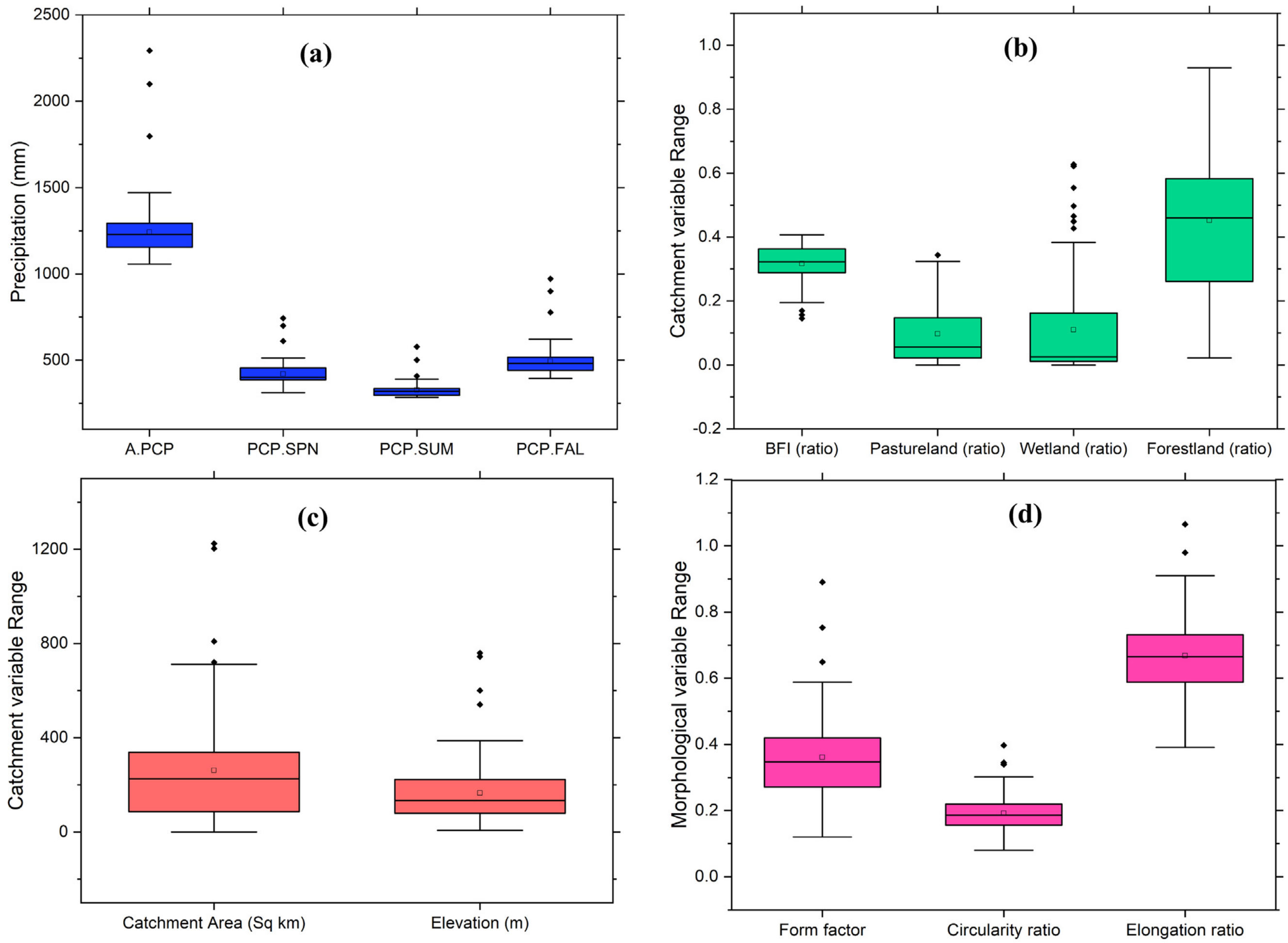

Fig. 6. Boxplot of important (a) climate variables: average annual precipitation (A.PCP), average spring precipitation (PCP.SPN), average summer precipitation (PCP.SUM), and average fall precipitation; (b and c) catchment variables: Base flow index, pastureland, wetland, forestland, catchment area, and elevation; (d) morphological variables: Form factor, circularity ratio, and elongation ratio over the Savannah River Basin. The spatial distribution of (a) Mean annual precipitation, (b) Base flow index, and (c) Stream order of watersheds across the Savannah River Basin.

4.4. Potential influence of climate, catchment and morphological variables

In this section, we investigated the potential influence of selected climate, catchment, and morphological variables on hydrological drought by using linear regression and backward stepwise selection method. Since multicollinearity exists between different climate, catchment, and morphological variables used in the study, we generated the correlation matrix of pairwise combinations of important variables based on the Pearson correlation coefficient (Fig. 8). The variables related to altitude such as, maximum elevation (MaxElev), minimum elevation (MinElev), and average elevation (Elev) are strongly correlated across the watersheds of SRB. Therefore, we selected Elev for further analysis. The candidate variables were selected based on their least collinearity nature with other variables as well as the higher Pearson correlation with hydrological drought durations for the watersheds of SRB. The above steps are illustrated with following example. The Pearson correlation coefficient between the elevation and forestland based on 104 watersheds located in the SRB is 0.7. However, the correlation strength between elevation and short term hydrological drought duration is higher in comparison to forestland. Therefore, watershed elevations were selected for the analysis. The linear and non-linear relationship between the candidate variables and the hydrological drought duration for short and medium term drought are shown in Figs. 9 and 10 respectively. The climate variables including A.PCP, PCP.FAL, and PCP.SPN and morphological variable S.Order showed a negative correlation with average drought duration. Whereas, catchment variables, such as BFI, pastureland, and wetland showed a positive correlation with average drought duration for SRI 1 and SRI 6 drought duration.

Subsequently, we investigated the potential influence of selected climate, catchment, and morphological variables separately on average drought duration for SRI 1, SRI 6, and SRI 12 drought by applying linear regression. These individual models are named as the climate, catchment and morphological models (Tables 5–7). Finally, we analyzed the relative impact of climate, catchment, and morphological variables on hydrological drought duration by applying backward stepwise selection method. This integrated model is named as combined model (Table 8).

4.4.1. Potential influence on short term drought

Several studies have been carried out to investigate the significant role of climate variables in hydrological drought propagation over a river basin (Wang et al., 2015; Sheffield et al., 2012). The present study also indicated that, the precipitation and evapotranspiration plays an important role in controlling the short term drought duration in the SRB (Table 5). In case of climate model, mean annual precipitation (A.PCP) showed comparatively higher significance (p-value) in controlling the hydrological drought duration. Therefore, below normal (average) precipitation in the SRB may lead the watersheds to a short term drought. The mean annual evapotranspiration (A.ET) also exhibited a

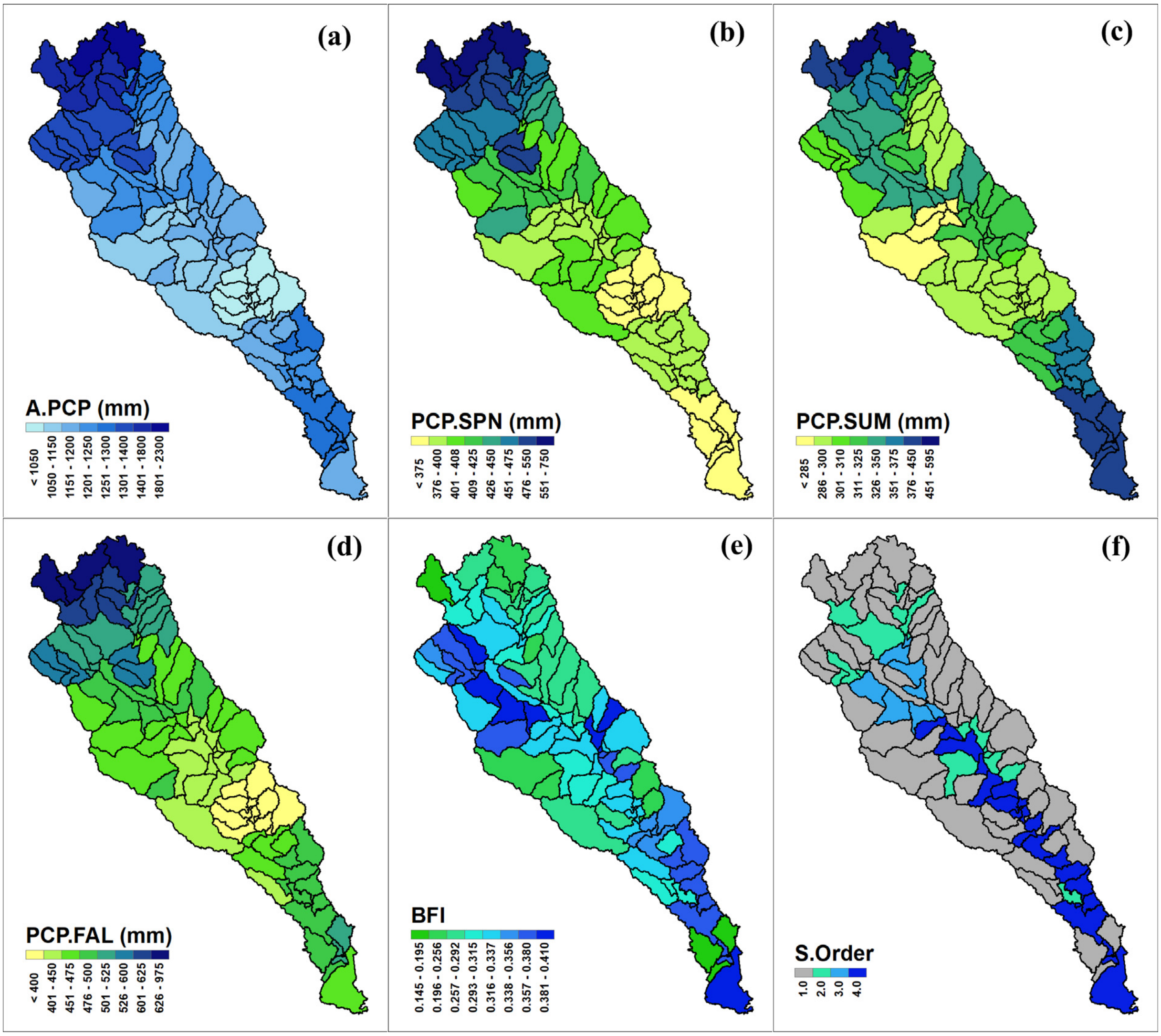

Fig. 7. The spatial distribution of (a) Mean annual precipitation (A.PCP), (b) average precipitation during spring (PCP.SPN), (c) average precipitation during summer (PCP.SUM), (d) average precipitation during fall (PCP.FAL) seasons. (e) Base flow index (BFI), and (f) Stream order of watersheds over the Savannah River Basin.

considerable significance in the climate model (Table 5). This situation will further direct to an additional loss of water stored in the soil layer, water bodies and lead the region to hydrological drought. Therefore, a combination of lower precipitation with higher evapotranspiration may increase the possibility of short term drought over the watersheds of SRB. Here, the climate model for predicting the duration of short–term drought produced a coefficient of determination (R^2) value of 0.12. Which indicates that, the short term drought cannot be predicted appropriately based on only climate variables. Whereas, the catchment model exhibited a R^2 value of 0.49 for predicting the short term drought duration over the watersheds (Table 6). The baseflow index (BFI) is identified as the most significant catchment variable (p-value = 5.03e − 07) for predicting the average duration of short term drought.

In this study, the BFI showed a positive correlation with the short term drought duration which is similar to Van Loon and Laaha (2015), Tallaksen and Van Lanen (2004), Barker et al. (2015). The BFI has a strong role in controlling the base flow, which plays an important role for hydrological drought. Moreover, the contribution of base flow for a long term denotes higher duration of drought in the watersheds. This may be a possible reason for the positive correlation of BFI with the short term drought for the SRB. Therefore, knowledge of base flow is crucial for developing catchment management strategies such as water quality management, reservoir management particularly during the drought period (Smakhtin, 2001).

The stream width has a significant influence on the short term drought (p-value = 1.63e − 07) with a negative correlation, which indicates that decrease in width of stream network may lead to longer duration of short term drought. The land use types such as, wetland and pastureland also has a major role on short term drought. Where, the wetland exhibited a positive correlation with hydrological drought duration, which indicates that the catchments with a larger area of wetland is more susceptible to hydrological drought. Similarly, pastureland also witnessed a positive correlation with short term drought duration for the watersheds of SRB. This may be due to increase in the evapotranspiration and decreases in the water yield (Zhang et al., 2016; Sriwongsitanon and Taesombat, 2011) due to pasturelands. The loss of water through evapotranspiration may reduce the streamflow contribution from agricultural/pastureland and finally lead to hydrological drought over the basin (Bagley et al., 2014).

Similar to the climate model, the morphological model also showed a lower value of coefficient of determination (0.18) for predicting the average duration for SRI 1 drought (Table 7). The significant morphological variables influencing the short term drought duration are stream order and relief ratio. Both the variables exhibited a negative correlation with the short term drought. It was observed that most of the

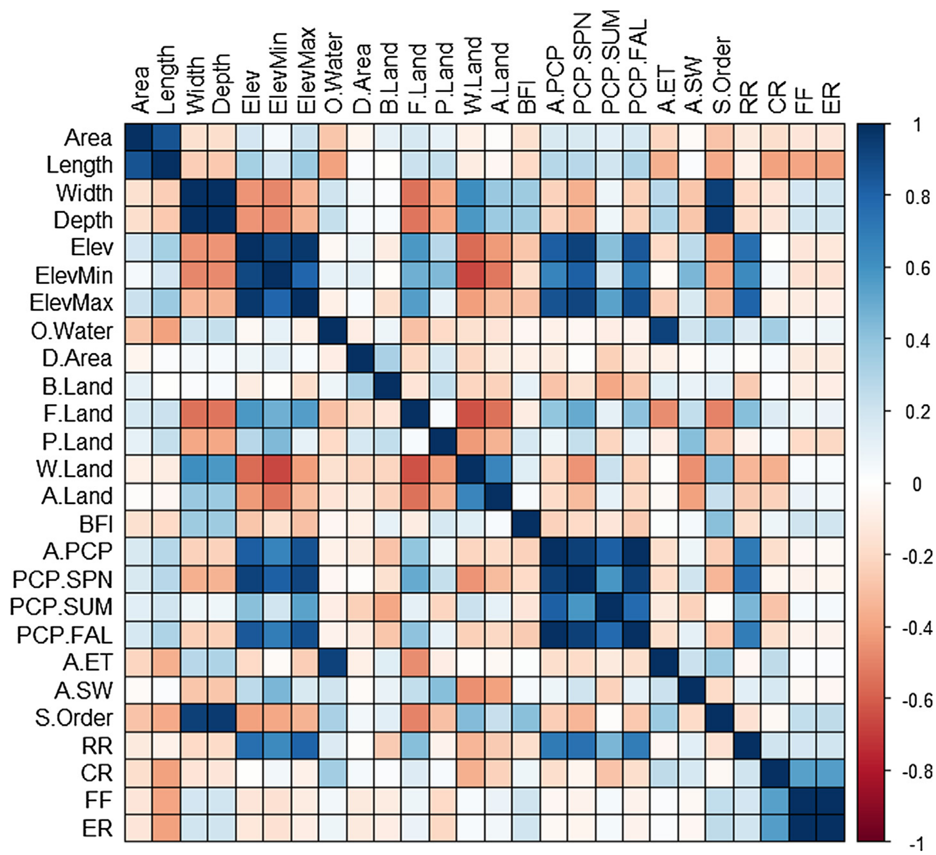

Fig. 8. The correlation matrix showing the Pearson correlation between the climate, catchment, and morphological variables.

watersheds with first or second-order streams are considerably influenced by the hydrological drought, and similar findings are highlighted in previous studies (Cowx et al., 1984; Hakala and Hartman, 2004). The maximum S.Order in the SRB is four (Fig. 5C), and the higher order streams are observed near to the mainstream network. This can be a possible reason for distribution of longer duration drought events towards the watersheds located away from the mainstream network. Although, the climate model and morphological models were less accurate in predicting the hydrological drought over the SRB, the catchment model was able to predict the hydrological drought duration with reasonable accuracy. In the following section we investigated the combined influence of climate, catchment, and morphological variables on hydrological drought.

The backward stepwise selection is performed to investigate the combined influence of climate, catchment, and morphological variables on hydrological drought duration. The proposed backward stepwise selection model was evaluated based on the Akaike Information Criterion (AIC). Overall, a combination of 8 climate, catchment, and morphological variables are selected (Table 8). It was observed that the combination of catchment and morphological variables with the climate variables significantly improved the prediction of hydrological drought duration ($R^2 = 0.58$) across the watersheds of SRB. Among all the variables, A.PCP, BFI, and S.Order seems to be the most significant climate, catchment, and morphological variables, which influence the drought duration for SRI 1 in the SRB.

4.4.2. Potential influence on medium and long term drought

In this section, potential influence of control of climate, catchment, and morphological variables on medium and long term drought duration are discussed. It was observed that summer precipitation (PCP.SUM) plays an important role in controlling the drought duration for SRI 6 in the SRB. The catchment variables such as elevation, catchment area, pastureland, and wetland are highly significant in controlling the medium term drought (Table 6). Where, the pastureland (p-value = $9.74e-06$) and elevation (p-value = $1.57e-06$) are identified as the most significant catchment variables. Similar to the short term drought, the catchment model for medium term drought also exhibited a higher R^2 (0.49) value. However, in the case of morphological model unlike the short term drought, circularity ratio (CR) and relief ratio (RR) are identified as the most significant morphological variables influencing the medium term drought duration and the morphological model was able to predict 14% ($R^2 = 0.14$) variability in hydrological drought duration.

The combined model selected six variables from the combination of climate, catchment, and morphological variables (Table 8) which influence the average drought duration for SRI 6 in the SRB. The combined model showed a coefficient of determination of 0.51, indicating that the model performance significantly improved through the addition of catchment and morphological variables with the climate variables. The result from the combined model showed that the PCP.SPN is the most important climate variable responsible for medium term drought over SRB. The percentage of pastureland is identified as the most significant variable pertaining to medium term drought and S.Order seems to be the only morphological variable that has potential influence on the hydrological drought duration for SRI 6.

The proposed climate model for long term drought suggests that the mean summer precipitation (PCP.SUM) is the only variable that has a potential influence on the long term drought (Table 5) in the SRB. The catchment and morphological models selected stream width and stream order as significant variables (Tables 6 and 7). The combined model also selected the same variables (stream width and stream order) based on the backward stepwise selection method (Table 8). However, the combined model was merely able to predict 12% variation in hydrological drought duration for SRI 12. Overall, it was observed that the linear models formed through the combination of climate, catchment, and morphological variables are capable for predicting the duration for

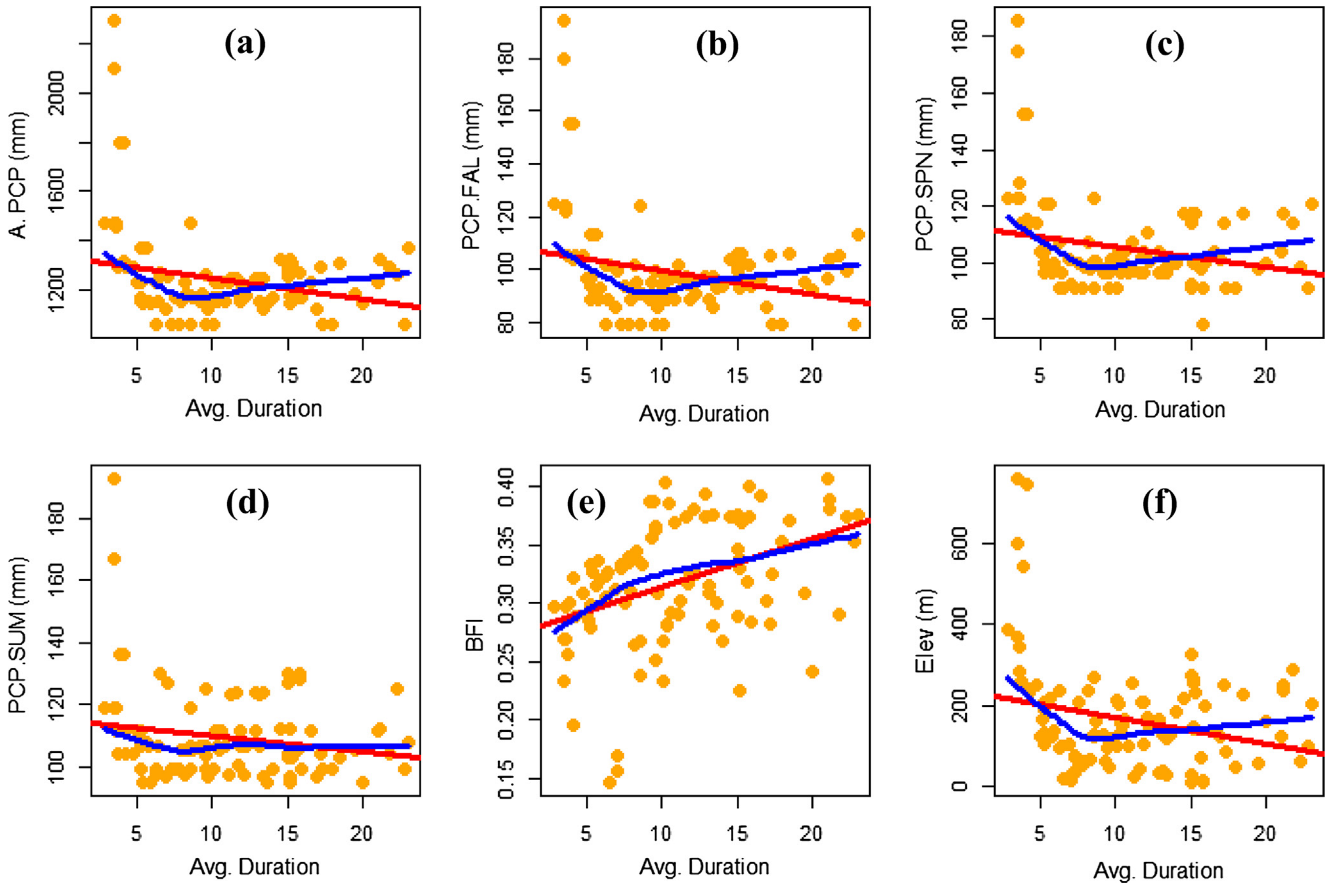

Fig. 9. Linear and nonlinear relation between average drought duration (Avg. Drought) for SRI 1 drought and (a) annual mean precipitation (A.PCP), (b) average precipitation during fall (PCP.FAL), (c) spring (PCP.SPN), and (d) summer (PCP.SUM) season, (e) base flow index (BFI), and (f) catchment elevation (Elev).

short and medium term drought. Nevertheless, long term drought duration showed comparatively less correlation with the variables considered in the study. In the following section, we performed CART for identifying the threshold of each variable for controlling the hydrological drought duration over the SRB.

4.5. Identification of critical threshold

The most influential climate, catchment, and morphological variables are selected using backward stepwise selection process. Then we applied the concept of classification and regression tree (CART) to identify the critical threshold associated with the selected variables. Using the CART approach, we generated three separate decision trees for short, medium, and long term drought to identify the threshold associated with the variables.

The model output of CART analysis by relating selected climate, catchment, and morphological variables and short term drought duration is shown in Fig. 11. The figure summaries the process of estimating the threshold of variables and the range of response (drought duration) with respect to each threshold. Here, the range of output drought duration for SRI 1 is represented in the form of a box plot. The decision tree approach identified BFI, S.Order, and A.PCP are the significant variables, which control the drought duration for SRI 1 over the watersheds of SRB. Among them, BFI was the most significant variable. Therefore, the first split in the decision tree was based on BFI (node 1) and the corresponding threshold is 0.344. For instance, when the BFI of the watersheds is less than or equal to 0.344 ($\leq$0.344), the growth of tree is towards the left (Fig. 11). Whereas, if the value of BFI is greater than 0.344 the tree is advancing to the right side. Here $p < 0.001$, represents the significance of the correlation between the split based on BFI and the average drought duration for SRI 1. The second split (node 2) of the decision tree is based on the morphological variable stream order, which indicates that, stream order is the second most significant variable controlling the short term drought across SRB. The threshold value of stream order was one. For instance, if a watershed has a stream order greater than one and the BFI is less than 0.344 the short term drought duration in that particular catchment will vary from 4 months to 8 months (Fig. 11). Whereas, if the stream order is less than or equal to one, the growth of the tree is towards left side. The third split in the decision tree (node 3) was based on the mean annual precipitation (A.PCP). Overall, the critical threshold of BFI, S.Order, and A.PCP are identified and it can be explained as follows in determining the duration of short–term drought.

If the BFI is $\leq$ 0.344, S.Order is $\leq$1 and A.PCP is $\leq$1308.44 mm then the duration of short term hydrological drought likes to be 12 months based on median (50th percentile, solid line within the boxplot) and it can vary from 6 months to 22 months. When the A.PCP is more than 1308.44 mm, the average duration of SRI drought will range from 2 to 4.5 months. The right branch of the node 2 elucidates that when the S.Order is greater than one and BFI is less than or equal to 0.344, the watersheds in SRB will experience a short term drought duration of 6 months (median).

The average annual precipitation in the SRB is 1240 mm per year and the threshold associated with annual precipitation is 1308 mm. Based on the right side branch of the first partition, the BFI greater than 0.344 resulted to a drought duration of 15 months for SRI 1. However, BFI has a positive correlation with the short term drought. Therefore, a minimum value of BFI likely to reduce the short term drought duration in the watersheds. The average BFI of SRB watersheds is observed as 0.317, which is less than the critical threshold of BFI. The results from

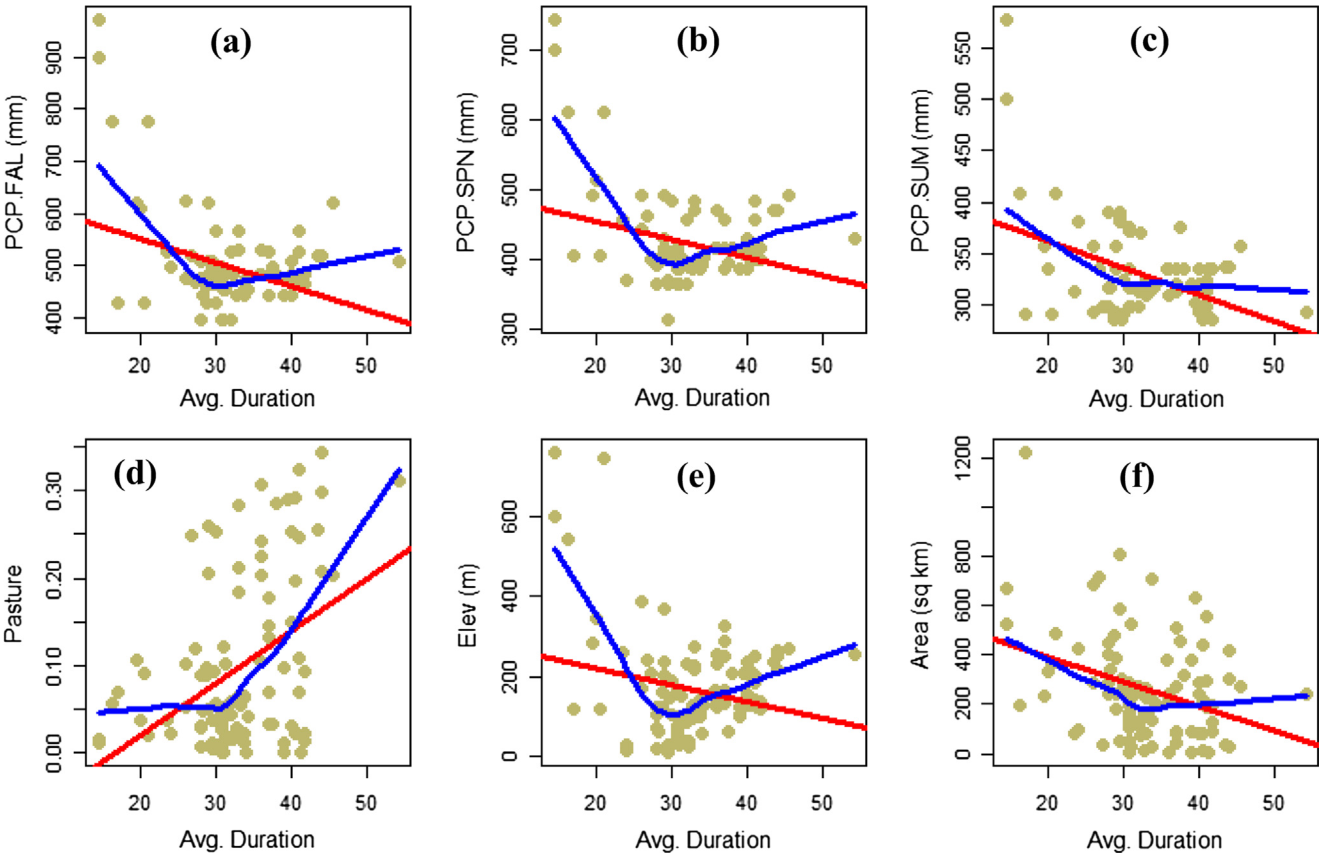

Fig. 10. Linear and nonlinear relation between average drought duration (Avg. Duration) for SRI 6 drought and (a) average precipitation during fall (PCP.FAL), (b) spring (PCP.SPN), and (c) summer (PCP.SUM) season, (d) pastureland, (e) catchment elevation (Elev), and (f) catchment area (Area).

Table 5
Model performance based on the climate variables (Climate model).

Drought class	Variable	p-value	R^2
SRI 1	A.PCP	0.00283 (**)	0.12
	A.ET	0.01049 (*)	
SRI 6	PCP.SUM	8.4e−06 (***)	0.18
SRI 12	PCP.SUM	0.0474 (*)	0.04

Table 6
Model performance based on the catchment variables (catchment model).

Drought class	Variable	p-value	R^2
SRI 1	Area	0.00336 (**)	0.49
	Elevation	0.028494 (*)	
	Width	1.63e−07 (***)	
	Pastureland	0.007718 (**)	
	Wetland	0.000249 (***)	
	BFI	5.03e−07 (***)	
SRI 6	Area	0.001687 (**)	0.47
	Elevation	1.57e−06 (***)	
	Pasture	9.74e−06 (***)	
	Wetland	0.000359 (***)	
SRI 12	Width	0.0416 (*)	0.04

Table 7
Model performance based on the morphological variables (Morphological model).

Drought class	Variable	p-value	R^2
SRI 1	S.Order	0.002463 (**)	0.18
	RR	0.000306 (***)	
SRI 6	RR	0.000497 (***)	0.14
	CR	0.002526 (**)	
SRI 12	S.Order	0.00594 (**)	0.07

linear regression analysis identified that S.Order is negatively correlated with drought duration. The decision tree output illustrates that if the S.Order is greater than one, the duration of SRI 1 drought reduces to 6 months and about 50% of the watersheds located in SRB has S.Order greater than one.

Fig. 12 illustrates the decision tree of average drought duration for SRI 6 and. It was identified that the variables such as Pastureland, PCP.SPN, catchment area, Wetland, and S.Order are significant for predicting the medium term drought duration across the watersheds of SRB. Therefore, the final tree consists of multiple nodes as well as thresholds associated with these variables. Pastureland showed maximum significance, and the first split of the tree is based on this variable with a threshold of 0.12 (12%). The linear analysis indicated that pastureland has a positive correlation with the medium term drought duration. In the Savannah River Basin, 73% of the catchments have pastureland of less than 12% and a minimum duration for medium term drought was observed in the catchments where the pastureland is less than 12%, and PCP.SPN is higher than 455 mm. This indicates that in those catchments, the storage plays an important role in reducing the drought duration because of less evapotranspiration from pastureland and higher precipitation during the spring season. On the other hand, that the longer drought duration is more prevalent in watersheds with pastureland more than 12% and S.Order one. Catchment area and wetland also influence medium term drought with a threshold of 209 km^2 and 3% respectively. Overall, the catchment variables seems to have a significant control on the drought duration for SRI 6 over the SRB.

Table 8
Model performance based on the combination of the variables (Combined model).

Drought class	Variable	p-value	R^2
SRI 1	Area	0.00168 (**)	0.58
	Width	0.00433 (**)	
	Pastureland	0.00302 (**)	
	Wetland	0.00033 (***)	
	BFI	3.01e − 09 (***)	
	A.PCP	0.00965 (**)	
	S.Order	1.39e − 10 (***)	
	C.Ratio	0.08345 (.)	
SRI 6	Area	1.74e − 05 (***)	0.51
	Width	0.03088 (*)	
	Pasture	9.59e − 09 (***)	
	Wetland	0.00039 (***)	
	PCP.SPN	9.05e − 08 (***)	
	S.Order	0.05303 (.)	
SRI 12	PCP.SUM	0.05074 (.)	0.13
	Width	0.12326	
	S.Order	0.00946 (**)	

Finally, the decision tree algorithm was applied to the drought duration for SRI 12 (Fig. 13). Unlike the linear regression approach, the decision tree approach could not identify a significant climate variable that influence long term drought. It was observed that S.Order (morphological variable) and Width of channels (catchment variable) are the important variables, which has potential control on the duration of long term drought.

5. Discussion and concluding remarks

In this study, a combination of hydrological and statistical models are utilized to quantify the potential influence of climate, catchment, and morphological variables and its associated threshold on short, medium, and long term hydrological drought. In the proposed model framework, the streamflow pattern over the Savannah River Basin is simulated based on a well calibrated SWAT model (Sohoulande Djebou, 2019) and the hydrological drought is quantified by applying the concept of Standardized Runoff Index. The SWAT model was selected as it can integrate different climate and catchment characteristics (e.g., topography, soil type, land use) to generate runoff at a higher spatial resolution (Lin et al., 2015; Zhou et al., 2013). For instance, the surface runoff over each HRU is estimated based on the modified curve number (CN) method with daily precipitation data based on soil hydrologic group, vegetation type, and land management practices. This method will produce an accurate representation of hydrology processes in each spatial unit. In addition, SWAT model was previously applied to quantify the potential influence of land use change and climate variability on the hydrological fluxes of Savannah River Basin (Veettil and Mishra, 2018). The SWAT model is calibrated using the monthly discharge data from 1993 − 2005 and validated for 2006–2013 and the goodness of fit statistics showed an acceptable agreement between observed (i.e. USGS flow) and SWAT simulated flow. Following the model simulation short, medium, and long term drought for each catchment was quantified based on the standardized runoff index (Shukla and Wood, 2008).

The statistical modeling framework incorporates a set of climate, catchment, and morphological variables to predict the hydrological drought for the watersheds located in Savannah River Basin. The results indicate that the catchment variables has higher influence to trigger the hydrological drought over the Savannah River Basin compared to

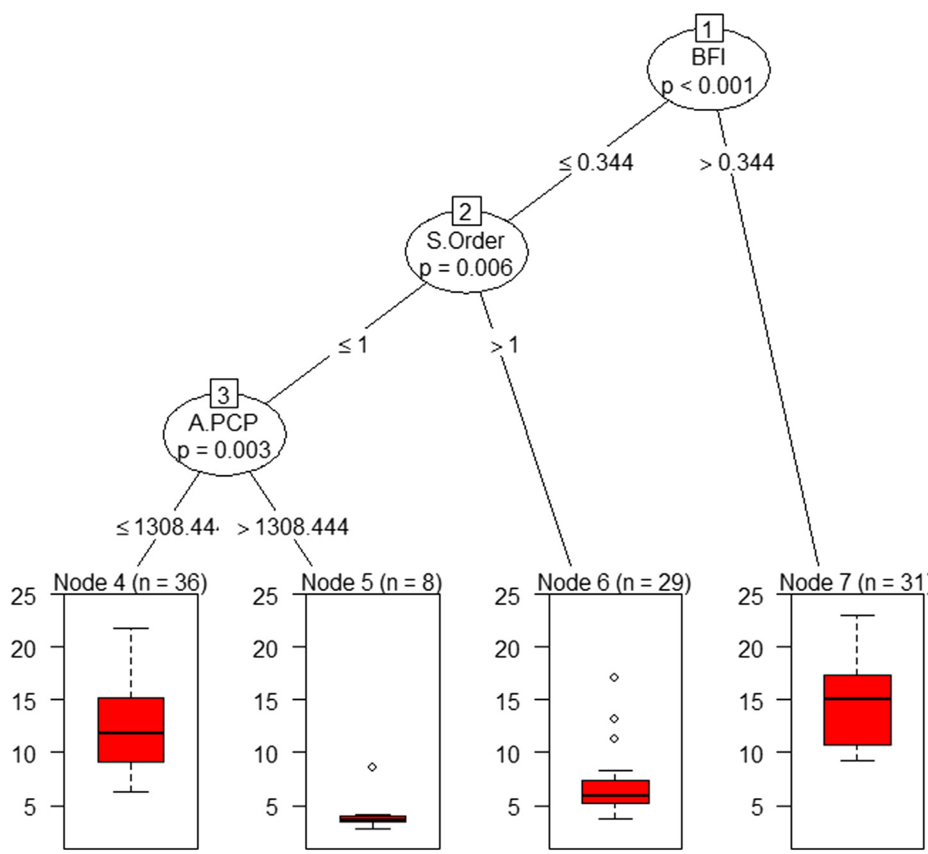

Fig. 11. Decision tree showing the threshold of climate, catchment, and morphological variables. The boxplot shows the duration of short term drought which are predicted based on the threshold.

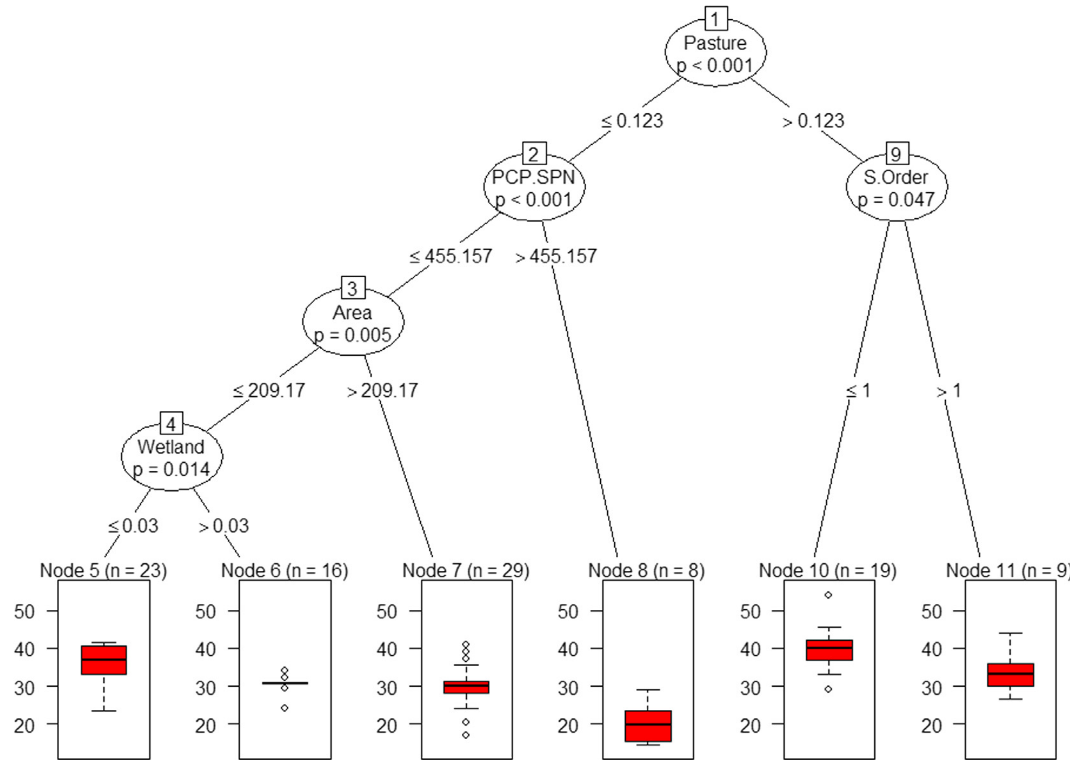

Fig. 12. Decision tree showing the threshold of climate, catchment, and morphological variables for medium term drought.

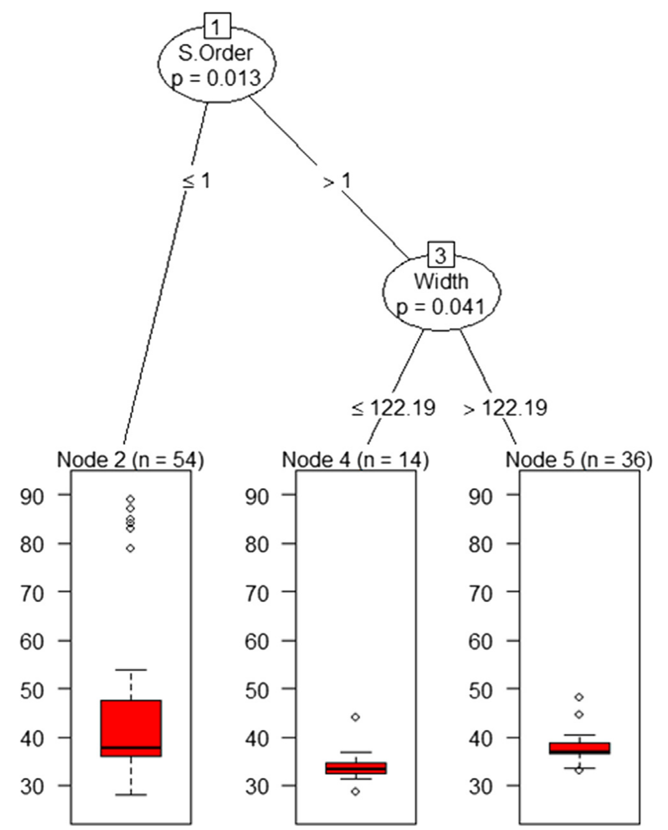

Fig. 13. Decision tree showing the threshold of catchment and morphological variables for long term drought.

climate and morphological variables. In addition, the combination of these variables can improve the prediction accuracy of short and medium term drought in the Savannah River Basin. Moreover, the study can be also be extended for an ungauged basin, where the availability of hydrological data is insufficient. However, the dominant factors in determining hydrological drought characteristics is highly dependent on scale. For example, on a global scale, drought duration might be more related to climate compared to catchment variables, whereas at a regional/river basin scale catchment or morphological variables may have more influence on the hydrological drought. Overall, the proposed modeling framework is useful for identifying the key role of climate, catchment, and morphological variables on the hydrological drought across the watersheds of Savannah River Basin. The following conclusions can be drawn from this study.

a) The linear models developed based only on climate variables may not be reliable for predicting the hydrological drought duration in the Savannah River Basin. Whereas, the performance of linear models can be improved by the addition of catchment and morphological variables. For example, in the case of short term drought, the performance of the model based on R^2 increased from 0.12 to 0.58 by including the catchment and morphological variables along with the climate variables.
b) The climate, catchment, and morphological variables, which has significant influence on the short term drought includes precipitation, base flow index, and stream order respectively. In the combined model, the stream order and baseflow index exhibited higher influence on the short term drought.
c) The catchment variables, such as pastureland, wetland, catchment area, and elevation showed significant influence on the average duration of medium term drought, which is derived based on SRI 6. The catchment model was able to predict 47% variability in the average hydrological drought duration for SRI 6, whereas the combined model improved the model performance to 51%. The catchment variable pastureland has a potential influence in controlling the medium term drought. It was also observed that the average precipitation during the spring season can be considered as a key variable that has potential influence on the average drought duration for SRI 6.

d) The average precipitation during the summer showed a significant control on the long term drought duration, which is derived based on SRI 12. In the combined model, the stream order and width of stream networks can have major influence on the long term drought duration.
e) The morphological variable stream order is identified as the only variable which has significant influence over short, medium and long term drought duration over the watersheds of Savannah River Basin. Which indicates the importance of including the morphological variables in predicting the hydrological drought in a river basin scale.
f) The classification and regression tree algorithm was used for identifying thresholds associated with climate, catchment, and morphological variables. The results indicate that the variables and associated thresholds influencing the hydrological drought varies for short, medium, and long term drought.

CRediT authorship contribution statement

Anoop Valiya Veettil: Data curation, Formal analysis, Methodology, Validation, Visualization, Writing - original draft, Writing - review & editing. **Ashok k. Mishra:** Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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