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Drought modeling – A review

Ashok K. Mishra *, Vijay P. Singh

Department of Biological and Agricultural Engineering, Department of Civil and Environmental Engineering, Texas A&M University, 2117 College Station, TX 77843, USA

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SUMMARY

In recent years droughts have been occurring frequently, and their impacts are being aggravated by the rise in water demand and the variability in hydro-meteorological variables due to climate change. As a result, drought hydrology has been receiving much attention. A variety of concepts have been applied to modeling droughts, ranging from simplistic approaches to more complex models. It is important to understand different modeling approaches as well as their advantages and limitations. This paper, supplementing the previous paper (Mishra and Singh, 2010) where different concepts of droughts were highlighted, reviews different methodologies used for drought modeling, which include drought forecasting, probability based modeling, spatio-temporal analysis, use of Global Climate Models (GCMs) for drought scenarios, land data assimilation systems for drought modeling, and drought planning. It is found that there have been significant improvements in modeling droughts over the past three decades. Hybrid models, incorporating large scale climate indices, seem to be promising for long lead-time drought forecasting. Further research is needed to understand the spatio-temporal complexity of droughts under climate change due to changes in spatio-temporal variability of precipitation. Applications of copula based models for multivariate drought characterization seem to be promising for better drought characterization. Research on decision support systems should be advanced for issuing warnings, assessing risk, and taking precautionary measures, and the effective ways for the flow of information from decision makers to users need to be developed. Finally, some remarks are made regarding the future outlook for drought research.

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* Corresponding author. Tel.: +1 979 661 6430.
E-mail addresses: akm.pce@gmail.com (A.K. Mishra), vsingh@tamu.edu (V.P. Singh).

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1. Introduction

Water scarcity has been frequently occurring these days in many parts of the world, partly because water demand has increased manyfold due to the growth in population and expansion of agricultural, energy and industrial sectors, and partly because of climate change and contamination of water supplies (Bates et al., 2008). The water scarcity is being further compounded by droughts which affect both surface water and groundwater resources and can lead to reduced water supply, deteriorated water quality, crop failure and disturbed riparian habitats (Riebsame et al., 1991). Therefore, understanding drought and modeling its components have drawn attention of ecologists, hydrologists, meteorologists, and agricultural scientists. Droughts are of great importance in water resources planning and management, and for a review of drought concepts the reader is referred to (Mishra and Singh, 2010).

This study reviews different components of drought modeling as shown in Fig. 1, and the paper is organized as follows. The discussion on drought forecasting given in Section 2 includes choosing input variables, different methodologies for drought forecasting and long-lead drought forecasting. Section 3 presents an overview of the probabilistic characterization of droughts, which includes univariate and bivariate drought analysis, and multivariate drought characterization using copulas, followed by a discussion on spatio-temporal drought analysis in Section 4 and drought modeling under climate change scenarios in Section 5. Section 6 reviews application of land data assimilation system for drought modeling, and Section 7 reviews methodologies for drought management. The review is concluded in Section 8.

2. Drought forecasting

Drought forecasting is a critical component of drought hydrology which plays a major role in risk management, drought preparedness and mitigation. There has been considerable work done on modeling various aspects of drought, such as identification and prediction of its duration and severity. However, a major research challenge is to develop suitable techniques for forecasting the onset and termination points of droughts. One of the deficiencies in mitigating the effects of a drought is the inability to predict drought conditions accurately for months or years in advance. For example, the National Oceanic and Atmospheric Administration (NOAA) issued forecasts of spring and summer droughts for five Midwestern states (USA) in the 2000s. However, in early June of 2000, heavy rains began to fall across the Midwestern drought area

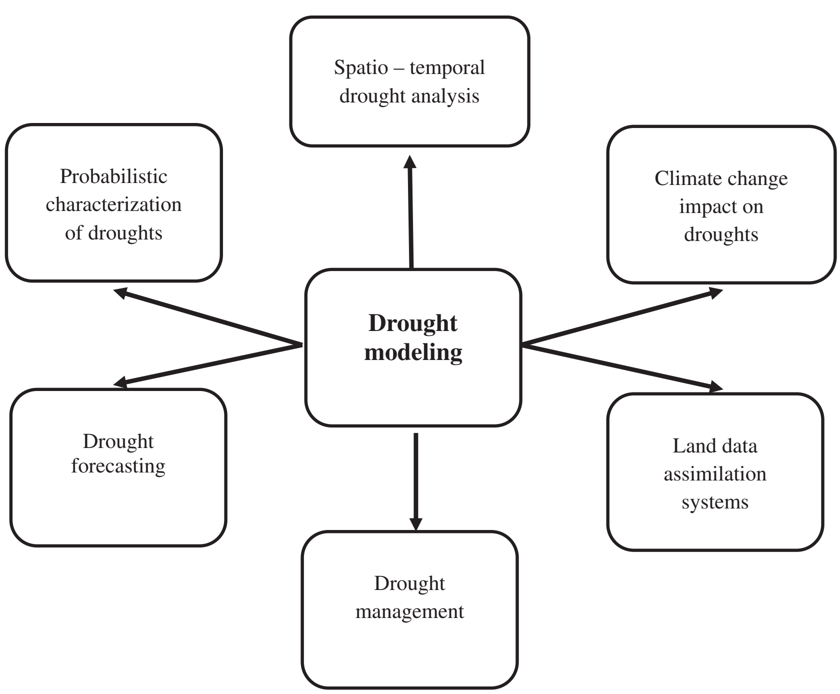


Fig. 1. Different components of drought modeling.

which reveals the rainfall totals for June ranked as the sixth wettest in the past 106 years (Changnon and Vonnahme, 2003). This may be due to the spatio-temporal variability of hydro-meteorological variables associated with the intensification of global hydrologic cycle. The different components of drought forecasting are shown in Fig. 2, which include input variables, methodology and the outputs obtained, and are discussed in the following subsections.

2.1. Input variables

The input variables for drought forecasting depend upon different types of droughts (Mishra and Singh, 2010) to be forecasted. The variables and associated types of drought include: (i) precipitation for meteorological drought analysis as precipitation deficits lead to a drought, (ii) stream flow, reservoir and lake level data for hydrologic drought analysis, (iii) groundwater levels for ground water drought, and (iv) soil moisture and crop yield for agricultural drought (several drought indices based on combinations of precipitation, temperature and soil moisture, have been derived in recent decades to study agricultural droughts that can be used for forecasting). Several drought indices have been derived for assessing the effect of a drought and defining different drought parameters, such as intensity, duration, severity and spatial extent. Some of the commonly used drought indices for drought forecasting include: Palmer Drought Severity Index (PDSI) (Palmer, 1965), Crop Moisture Index (CMI) (Palmer, 1968), Standardized Precipitation Index (SPI) (McKee et al., 1993), Soil Moisture Drought Index (SMDI) (Hollinger et al., 1993) and Vegetation Condition Index (VCI) (Liu and Kogan, 1996). Also the reservoir inflow can be used for real-time drought forecasting in multireservoir operations (Huang and Yuan, 2004; Huang and Chou, 2005). For a detailed discussion on drought indices the reader is referred to Heim (2002) and Mishra and Singh (2010). Also, climate indices like El Nino-Southern Oscillation (ENSO), which is numerically defined by the Southern Oscillation Index (SOI), Sea Surface Temperature (SST), North Atlantic Oscillation (NAO), Pacific Decadal Oscillation (PDO), Inter-decadal Pacific Oscillation (IPO) and Atlantic Multi-decadal Oscillation (AMO) are used in addition to the hydro-meteorological variables for long-lead drought forecasting.

2.2. Methodology

Once the input variables are defined it is useful to discuss different methodologies and their advantages as well as limitations for drought forecasting. The following section briefly discusses different methodologies as well as their applications in drought forecasting.

2.2.1. Regression analysis

The relationship between two or more quantitative variables, a dependent variable whose value is to be predicted, and independent variables about which information is available can be explored using regression analysis. For example, a multiple regression predicts one variable from two or more independent variables, $Y = a + bX_1 + cX_2 + dX_3$, where Y is the dependent variable; X_1, X_2 and X_3 are the independent variables; and a, b, c and d are constants. Here the dependent variable is a drought

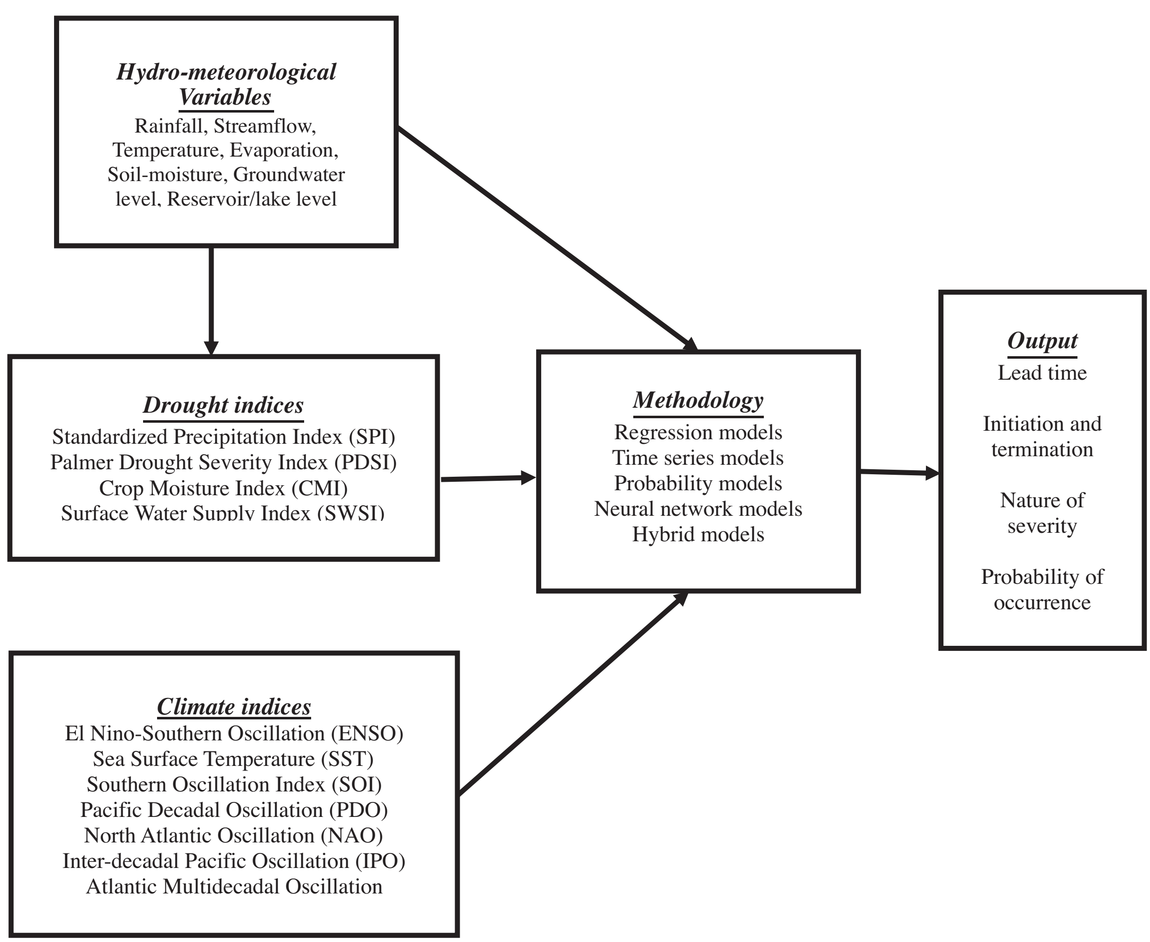


Fig. 2. Different components for drought forecasting.

quantifying parameter, for example, a drought index, whereas the independent variables are explanatory variables for the drought quantifying parameter (i.e., precipitation, streamflow and soil moisture). Some of the applications of regression analysis for drought forecasting are discussed below.

Kumar and Panu (1997) developed a regression model considering the grain yield of a main crop as agricultural drought quantifying parameter and variables affecting the grain yield in the region as explanatory variables for agricultural drought forecasting. This regression model was able to predict the grain yield of the main crop several months ahead of crop harvesting operations and was, in turn, able to assess the agricultural drought severity as mild, moderate, or severe. In another study, Leilah and Al-Khateeb (2005) investigated the relationship between wheat grain yield and its components under drought conditions of Saudi Arabia. The onset prediction of drought in northeast Brazil was studied by Liu and Negron-Juarez (2001) using multiple linear regression by considering the Normalized Difference Vegetation Index (NDVI) as dependent variable to quantify drought based on the various ENSO indices as independent variables which include: Niño 3.4, Southern Oscillation Index (SOI), North Atlantic Sea Surface Temperature (NATL), South Atlantic Sea Surface Temperature (SATL), and Dipole 2 (DIP2). Although regression analysis has been a commonly used method, there are several limitations. One of the limitations is the assumption of linearity between predictor and predictand which makes it less capable for long-lead forecasting. The other limitation is conceptual, specifically the difficulty in understanding underlying causal mechanisms and multicollinearity.

2.2.2. Time series analysis

Time series models have been commonly used in a broad range of scientific applications, including hydrology, however, applications for drought forecasting have been limited. Some of the major advantages of time series models include their systematic search capability for identification, estimation, and diagnostic check for model development (Mishra and Desai, 2005a). Time series models, like Autoregressive Integrated Moving Average (ARIMA), effectively consider serial linear correlation among observations; whereas Seasonal Autoregressive Integrated Moving Average (SARIMA) models can satisfactorily describe time series that exhibits nonstationarity both within and across seasons. Two types of stochastic models are commonly used (Box et al., 1994) which are briefly discussed here.

(i) General non-seasonal ARIMA model: It may be written as:

$$\phi(B)\nabla^d z_t = \theta(B)a_t \tag{1}$$

In short, a seasonal ARIMA (SARIMA) model is: ARIMA $(p, d, q)(P, D, Q)_s$, where (p, d, q) is the non-seasonal part of the model; and $(P, D, Q)_s$ is the seasonal part of the model.

(ii) General seasonal ARIMA model may be written as:

$$\phi_P(B)\Phi_P(B^s)\nabla^d\nabla_s^D Z_t = \theta_q(B)\Theta_Q(B^s)a_t \tag{2}$$

where $\phi(B)$ and $\theta(B)$ are polynomials of order p and q, respectively; $\Phi(B^s)$ and $\Theta(B^s)$ are polynomial in B^s of degrees P and Q, respectively; p is the order of non-seasonal autoregression; d is the number of regular differencing; q is the order of non-seasonal moving average; P is the order of seasonal autoregression; D is the number of seasonal differencing; Q is the order of seasonal moving average; and s is the length of season.

Using time series models a time series of a drought quantifying parameter can be used for drought forecasting, depending upon the previous observations. Rao and Padmanabhan (1984) used the stochastic nature of yearly and monthly Palmer's drought index (PDI) as drought quantifying parameter and used stochastic models to forecast and simulate PDI series. Mishra and Desai (2005a) developed linear stochastic models (ARIMA and SARIMA) for forecasting droughts in the Kansabati River basin in India with the use of the Standardized Precipitation Index (SPI) series as drought quantifying parameter and a similar approach was also adopted recently in Turkey (Durdu, 2010). The models can be used to forecast droughts up to 2 months of lead-time with reasonable accuracy. Modarres (2007) used an ARIMA model for streamflow drought forecasting in Zayardehrud River in western Isafan, Iran. Using the Vegetation Temperature Condition Index (VTCI) as drought quantifying parameter, Han et al. (2010) used an ARIMA model to forecast droughts in the Guanzhong Plain in China. It is also possible to forecast streamflow at different lead times as a first step and then deriving corresponding drought properties. Using a multiplicative Seasonal Autoregressive Integrated Moving Average model, Fernández et al. (2009) forecasted streamflow with a 12 month lead time and then derived different drought indices based on streamflow mean, monthly streamflow mean and standardized streamflow index. However, because of the strength and flexibility associated with time series models, it depends on one's capability in terms of identification, estimation and diagnostic checks to select the best model from amongst candidate models.

2.2.3. Probability models

Probability models are useful for drought forecasting due to their complex nature as well as to quantify uncertainties associated with hydro-meteorological variables causing droughts. Commonly Markov chain models have been used for drought forecasting. A Markov chain is a stochastic process having the property that the value of the process at time t, X_t, depends only on its value at time $t-1$, X_{t-1}, and not on the sequence of values X_{t-2}, X_{t-3} ... X_0 that the process passed through in arriving at X_{t-1}. This can be written as (Haan, 2002):

$$\begin{aligned} &Prob(X_t = a_j|X_{t-1} = a_i, X_{t-2} = a_k, X_{t-3} = a_{1,\ldots,}X_0 = a_q) \\ &\qquad = Prob(X_t = a_j|X_{t-1} = a_i) \end{aligned} \tag{3}$$

The conditional probability, $Prob(X_t = a_j|X_{t-1} = a_i)$, gives the probability that the process at time t will be in "state j" given that at time $t-1$ the process was in "state i". The term $Prob(X_t = a_j|X_{t-1} = a_i)$ is commonly called one-step transition probability. That is, it is the probability that the process makes the transition from state a_i to state a_j in one time period or one step, which is commonly denoted by p_{ij}. Transition probabilities are basic to the structure of Markov chains.

Gabriel and Neumann (1962) were among the first to apply Markov models for dry spell analysis. A non-homogeneous Markov chain model was used by Lohani and Loganathan (1997) based on the Palmer Drought Severity Index to characterize the stochastic behavior of droughts for an early warning system in the form of all possible sequences of drought progression which was useful for drought management. Statistical properties of drought indices can be obtained by conditioning monthly drought indices on large-scale atmospheric circulation patterns which can predict droughts under the impact of climate change scenarios (Bogardy et al., 1994). Using the first-order Markov chains Lohani et al. (1998) forecasted drought conditions for future months, based on the current drought class described by the Palmer index. In another study, Sen (1990) predicted possible critical drought durations that may result from any hydrologic phenomenon during any future period using second order Markov chains. Cancelliere et al. (2007) forecasted seasonal SPI by computing transition probabilities from a current drought condition to another in the future based on the statistics of the underlying monthly precipitation.

Paulo et al. (2005) derived a conditional scheme using Markov chain modeling for predicting short term drought classes.

Using homogeneous Markov chain models Steinemann (2003) proposed drought trigger preparedness plans at the basin scale to characterize the probabilities of drought transition. Banik et al. (2002) analyzed probabilities of transitions from a dry week to a non-dry week to develop an index of drought proneness for a given region, and Ochola and Kerkides (2003) to predict the number and lengths of dry spells. Moreira et al. (2006) applied a loglinear modeling approach to understand probabilities of transition between drought classes in order to detect a possible trend in time evolution of droughts which could be related to climate change.

2.2.4. Artificial neural network model

Neural networks are a class of flexible nonlinear models that can adaptively discover patterns from the data. Theoretically, it has been shown that given an appropriate number of nonlinear processing units, neural networks can learn from experience and estimates any complex functional relationship with high accuracy. For a detailed review of artificial neural network (ANN) models and their application in hydrology the reader can refer to (ASCE, 2000; Govindaraju and Rao, 2000). Generally, a three-layer feed-forward model, which consists of input layer, hidden layer and output layer, is used for forecasting purposes. The input nodes can be: (i) suitable previously lagged observations of drought quantifying time series, (ii) explanatory variables for quantifying drought, or (iii) a combination of both (i) and (ii). The hidden nodes with appropriate nonlinear transfer functions are used to process the information received by the input nodes, while the output layer is used for forecasting for different lead times.

Different types of neural networks can be used and the discussion is beyond the scope of the present review. Some of the applications of ANN models in drought forecasting include: Morid et al. (2007) predicted quantitative values of drought indices using different combinations of past rainfall, Effective Drought Index (EDI) and Standard Precipitation Index (SPI) in preceding months, and climate indices, such as SOI and NAO index as input layer. In another study, Mishra and Desai (2006) compared linear stochastic models with recursive multistep neural network (RMSNN) and direct multistep neural network (DMSNN) for drought forecasting and observed that RMSNN was useful for short term drought forecasting, while DMSNN was useful for long-term drought forecasting. Although neural networks require less formal statistical training and are able to detect complex nonlinear relationships between dependent and independent variables, the major disadvantages include their black box nature, empirical nature of model development, computational burden, and proneness to over fitting.

2.2.5. Hybrid models

Hybrid models are useful in extracting advantages of individual models for predicting droughts with better accuracy as well as for higher lead time in comparison to individual models. For example, wavelet transform methods can capture useful information at various resolution levels, whereas a neural network model can forecast the decomposed subsignals at various resolution levels obtained from wavelets and reconstruct forecasted subsignals to the original series. Applicability of this hybrid model was demonstrated by Kim and Valdes (2003) to forecast droughts using PDSI as a drought index and the results improved the ability of neural networks to forecast an indexed regional drought. Mishra et al. (2007) developed a hybrid model, combining a linear stochastic model and a nonlinear artificial neural network to forecast droughts with a Standardized Precipitation Index series using the advantages of both stochastic and ANN models. The hybrid model was found to forecast droughts with greater accuracy. Ozger et al. (in preparation) developed a wavelet and fuzzy logic (WFL) combination model for long lead-time drought forecasting using Palmer drought series. The idea of WFL is to separate each predictor and predictand into their bands and then reconstruct the predictand series by using its predicted bands. The strongest frequency bands of predictors and predictand were determined from the average wavelet spectra. Comparison between a WFL and ANN model and a coupled wavelet and ANN (WANN) model showed that WFL was more accurate for drought forecasting with long lead times. To demonstrate, comparison (between Fuzzy logic (FL) model and hybrid (WFL) model) based on 12 month lead-time forecast considering Palmer index as drought variable in Texas is shown in Fig. 3 (Ozger et al., in preparation). It can be observed that the hybrid model (WFL) is able to capture peaks better than an individual model. The hybrid method, using an Adaptive NeuroFuzzy Inference System (ANFIS) for drought forecasting using SPI, was found to perform better than the neural network model when applied in Central Anatolia, Turkey (Bacanli et al., 2009).

2.2.6. Long-lead drought forecasting

Long-lead drought forecasting is possible using climate indices as well as the periodic nature of hydro-meteorological variables and is discussed in the following section.

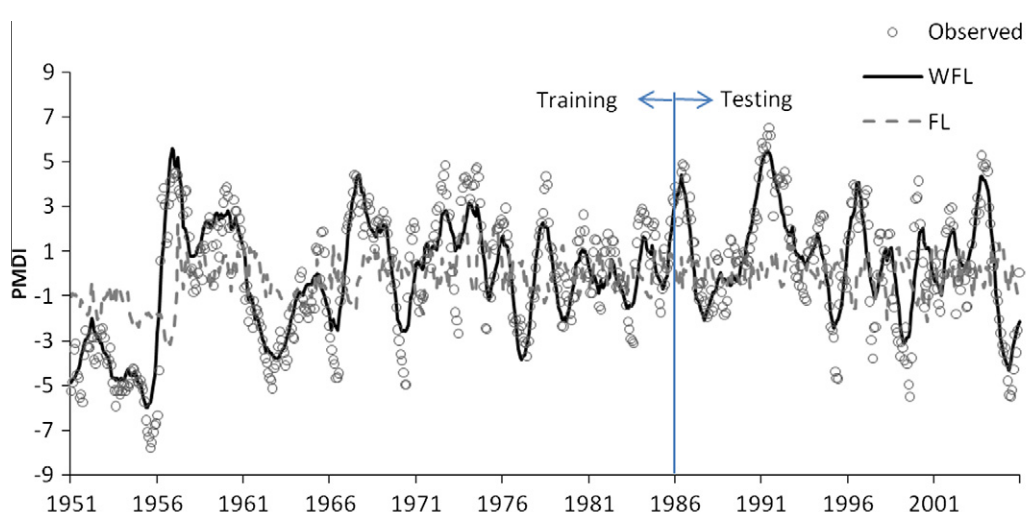


Fig. 3. Observed and 12-month ahead forecasted PMDI values using FL and WFL models.

2.2.6.1. Role of climate indices. Drought indices, derived over decades, have rainfall as a major parameter causing droughts (Mishra and Singh, 2010). Therefore long-lead drought forecasting is possible, if rainfall is predicted a long time in advance. Around the globe, precipitation has been shown to be related to broad scale atmospheric phenomena, such as El Nino-Southern Oscillation [ENSO], Sea Surface Temperature (SST), and Geopotential Height (GpH) (Ropelewski and Halpert, 1996). A relatively strong statistical relationship between ENSO, SSTs and rainfall has aroused considerable interest in long-range rainfall forecasting (Palmer and Anderson, 1994; Hastenrath, 1995; Goddard et al., 2001). However, the relation of large climate indices to rainfall varies from one region to another, for example, ENSO is a good indicator of droughts in Australia (Chiew and McMahon, 2002), but not necessarily in central and northern parts of Asia (Morid et al. (2006). Several studies demonstrated that ocean–atmosphere forcing by persistent Sea Surface Temperature (SST) influenced the timing of drought events, and their duration and magnitude over continental regions were largely governed by land–atmosphere feedbacks (Ferguson et al., 2010).

Improvements in climate forecasts have created potential to improve seasonal to interannual drought forecasting for efficient water resources management and this potential remains largely untapped. Barriers to the broad use of drought forecasts include difficulties in understanding, applying, evaluating, and trusting forecasts (Briggs and Wilks, 1996; Carbone and Dow, 2005; Steinemann, 2006). In order to have better drought forecasting, one should be able to forecast ENSO activities (e.g., Cane and Zebiak, 1985). Currently there are different approaches for ENSO prediction, for example: (i) statistical models, (ii) physical ocean models/statistical atmosphere models, and (iii) physical coupled ocean/atmosphere models. Latif et al. (1994) described the performance of different ENSO prediction schemes, ranging from purely statistical schemes to comprehensive coupled ocean–atmosphere models. It was shown that simple indices of ENSO were predictable on average about 1 year in advance. The most successful schemes, the fully physical coupled ocean–atmosphere models, showed a significant but modest skill even beyond 1 year. Similarly, global circulation anomalies forced by tropical SSTs playing an important role in the major North American droughts and therefore the successful longer lead-time drought prediction depends on several factors (Schubert et al., 2007): a successful SST prediction and simulation of the global circulation response to the SST anomalies, and a proper account of the land–atmosphere interaction that converts a precipitation anomaly into a meteorological or hydrological drought.

Applications of Global Climate Models (GCMs) are quite useful in advancing our understanding of the dynamical mechanisms governing hydro-climatic variability (Hoerling and Kumar, 2003; Schubert et al., 2009; Seager, 2007) as well as observing droughts on decadal basis (Mishra and Singh, 2009a). The GCMs are generally able to reproduce observed or expected patterns of drought with high fidelity (Herweijer et al., 2006; Seager et al., 2005), albeit with some notable exceptions over North America (Cook et al., 2008 and Seager et al., 2008), when forced with either observed (Herweijer et al., 2006) or idealized (Schubert et al., 2009) Sea Surface Temperature (SST) patterns. These studies helped highlight the important role played by SSTs in the Pacific (Herweijer et al., 2007 and Seager, 2007) and North Atlantic (Kushnir et al., 2010) Ocean basins and likely to play an important role for longer lead-time drought forecasting. However there are several advantages of using GCMs to study drought dynamics (Cook et al., in press) as based upon first principles, results from GCMs can be independently compared and verified against observational data sets and empirical studies and providing direct and independent insight into the physical mechanisms.

There is a significant improvement in long range drought forecasting after setting up of the Climate Variability and Predictability (CLIVAR) working group (http://www.clivar.org/about/objectives.php) based on the specific objectives: (a) to develop our understanding of climate variability, to apply this to provide useful prediction of climate variability and change through the use of improved climate models, and to monitor and detect changes in our climate system and (b) to extend the range and accuracy of seasonal to interannual climate prediction through the development of global coupled predictive models. In a recent study by the US Climate Variability and Predictability working group (Schubert et al., 2009) addressed a number of uncertainties regarding the impact of SST forcing and the role of land–atmosphere feedbacks on regional drought based on a series of Global Climate Model simulations.

Advances in the computing power, coupled with increased data availability, have led to a recent revolution in long-range weather prediction (Johansson et al., 1998; Barnston et al., 1999) which can be explored for drought forecasting as well. Several research highlighted spatio-temporal changes in teleconnection pattern between climate indices and hydro-meteorological variables (Rajagopalan et al., 2000 and Mishra and Singh, in press) and this can complicate long range drought forecasting, therefore the models needs to be updated. Some of the applications of climate indices in different parts of the world for drought forecasting are discussed below:

Australia: Cordery (1999) found strong relationships between a global parameter, SOI, and local parameter, GpH, in one season and precipitation in the next season in parts of eastern Australia. The success of this forecasting scheme is apparent in all four seasons of the year. This form of forecasting, which is based on the partitioning of observed data, has the potential to provide reliable 3-month ahead forecasts of precipitation for large regions. This long range forecasting of rainfall is suitable for drought prediction. Kiem and Franks (2004) investigated multi-decadal variability of drought risk by analyzing the performance of a water storage reservoir in New South Wales, Australia, during different climate epochs defined with the use of the Inter-decadal Pacific Oscillation (IPO) index. The results indicated that the IPO modulation of both the magnitude and frequency of ENSO events had the effect of reducing and elevating drought risk on multidecadal time scales. This study is very useful for hydrologic drought forecasting. There is enough scope to increase the lead time of drought forecasts for decision support using parsimonious data models that capture the governing climate processes at a regional scale. Based on different predictors, which include spatial datasets of precipitation, Sea Surface Temperature anomaly (SSTA) patterns over the Indian and Pacific Oceans, temporal and spatial gradients of outgoing long-wave radiation (OLR) in the Pacific Ocean, and the far western Pacific wind-stress anomaly, Barros and Bowden (2008) improved drought forecasting models in the Murray–Darling Basin (MDB) in Australia up to 12 months in advance.

Mediterranean region: Eshel et al. (2000) developed a dynamically statistical forecasting scheme for eastern Mediterranean winter rainfall based on North Atlantic sea level pressure precursors. The resulting forecasts were robust and statistically significant at a 13-month lead time, and improved at a 7-month lead, and these forecasts formed a foundation for an operational early warning system for eastern Mediterranean droughts.

USA: Pongracz et al. (1999) developed fuzzy rule based modeling for the prediction of regional droughts based on Palmer index characterization using two forcing inputs, ENSO and large-scale atmospheric circulation patterns (CPs) in a typical Great Plains state of Nebreska, USA. Different climate indices have varying impact on the river basin. For example, Balling and Goodrich (2007) observed that for the Colorado River basin as a whole, the Pacific Decadal Oscillation (PDO) explained more variance in Palmer

Hydrological Drought Index (PHDI) than did ENSO and Atlantic Multidecadal Oscillation (AMO) using principal component analysis. Steinemann (2006) reported the use of climate forecasts for drought management in the state of Georgia. Özger et al. (2009) derived the spatial structure of teleconnections of both El Niño Southern oscillation (ENSO) and Pacific decadal oscillation (PDO) for drought forecasting during the 20th century for the state of Texas. Lag times and correlation coefficients between droughts and climate indices were detected. This information plays a significant role for drought forecasting using climate indices.

United Kingdom: Wedgbrow et al. (2002) investigated spatial and temporal relationships between large-scale North Atlantic climatic indices, drought severity and river flow anomalies in England and Wales. It was observed that the preceding winter values of the Polar Eurasian (POL) index, North Atlantic Sea Surface Temperature Anomalies (SSTA) and to a lesser extent NAO provided indications of summer and early autumn drought severity and river flow anomalies in parts of northwest, southwest and southeast England.

2.2.6.2. Importance of periodicity in drought forecasting. Often hydro-climatic variables are periodic in nature and this characteristic can be explored further for drought prediction. Periodicity varies from 2 to 3 year (QBO = Quasi-Biennial Oscillation) to several tens of years, with varying proportions of the various amplitudes for different regions. Some of the earlier studies include: Lansford (1979) predicted a possible drought in the 1990s in parts of USA based on a 20–22 year periodicity as evident from tree ring analysis. In another example, based on historical records of rainfall and general atmospheric circulation patterns in different parts of the world, Winstanley (1973a,b) observed a 200 year cycle and concluded that a severe drought would be likely to occur in about 2030 AD in Sahel and north-western India. A review by Siscoe (1978) indicated roughly a 20 year periodicity for expansion and contraction of areal droughts in western USA, which seemed to be associated with the 22 year Hale sunspot cycle. Gray (1976) found periodicities of 40, 50, and 100 year in the annual rainfall of southeast England for 1840–1970 and used these for forecasting decadal average rainfall for the next few decades. Vines (1977) predicted that a severe drought was expected in Victoria (Australia) in near future (after 1977), which seems to have come true, with a severe drought in 1982.

2.2.7. Use of data mining for selection of predictors

Different types of data sets are used in drought modeling at different spatial and temporal scales which can make larger data size and high dimensionality, and which needs to be updated regularly. Therefore, identification of effective predictors is a major component of forecasting models and to identify them data mining can be considered a powerful technology which helps in extracting predictive information from large databases of atmospheric and oceanic parameters that cause droughts.

Using data mining techniques, Farokhnia et al. (2010) identified effective grids of Sea Surface Temperature (SST) and Sea Level Pressure (SLP) as predictors and using these as input to a hybrid model (Adaptive NeuroFuzzy Inference System, ANFIS) to forecast possible droughts in Iran. Similarly, Dhanya and Nagesh Kumar (2009) used a data mining approach to derive association rules for five homogenous regions of India by making use of different climatic indices, i.e., Darwin sea level pressure, North Atlantic Oscillation, Nino 3.4 and SST values and observed that these climate indices were occurring as antecedents for drought episodes, with different combinations and confidence values. In order to reduce the trial and error effort in selecting predictors, Vasiliades and Loukas (2010) used a data mining methodology to select the input variables and the training data length in order to evaluate the best mean squared error that can be achieved by a smooth model on any unseen data for a given selection of inputs. The application further included deriving several nonlinear models for forecasting droughts from 1 to 12 month lead time in Thessaly region, Greece. Using association rules, Tadesse et al. (2004) identified the relationship between oceanic parameters and drought indices in Nebraska, USA. The study could identify drought episodes separate from normal and wet conditions, and find relationships between drought indices (SPI and PDSI) and multiple oceanic indices in a manner different from traditional statistical associations. The study demonstrated that SOI, MEI and PDO have relatively stronger relationships with drought episodes over selected stations in Nebraska.

3. Probabilistic characterization of droughts

Droughts exhibit a typical probabilistic characteristic (Sen, 1980a; Loaiciga and Leipnik, 1996; Chung and Salas, 2000; Mishra et al., 2009). Probabilistic characterization of droughts is extremely important, primarily in those regions where accurate water resources planning and management requires a detailed knowledge of water shortages. There has been a significant amount of research on the probabilistic characterization of droughts since Yevjevich (1967) introduced concepts and the theory of runs (e.g., Downer et al., 1967; Llamas and Siddiqui, 1969; Sen, 1976, 1980b; Dracup et al., 1980a,b; Frick et al., 1990; Loaiciga and Leipnik, 1996; Fernández and Salas, 1999a,b). Basically parameters essential for characterizing a drought include: severity, duration, intensity, and interarrival time which are essentially, calculated using the theory of runs (Mishra and Singh, 2010). Different probabilistic analyses can be carried out to characterize different aspects of droughts (Fig. 4) which include: (i) estimation of return periods for drought parameters and univariate drought analysis, (ii) bivariate drought analysis which deals with two drought parameters, (iii) multivariate drought analysis using copulas which include more than two drought parameters, and (iv) spatio-temporal drought analysis which are discussed below.

3.1. Return period and frequency analysis

Return periods are in common use in hydrologic engineering and are an important parameter for design of water resource systems. However, the estimation of return periods depends on the availability of historical data, which is, usually, the most important limitation to directly inferring the probability of extreme episodes of droughts. The following section discusses the definitions associated with return periods, followed by examples of applications and methodology of return periods.

3.1.1. Definition of return period in drought analysis

A return period in drought analysis can be defined in different ways for different applications. When the concept of return period is applied to drought-related variables, it indicates the average time between the occurrences of events with a certain magnitude or less (Haan, 2002). The definition by Lloyd (1970), Loaiciga and Marino (1991) and Shiau and Shen (2001) assumed the return period as the average elapsed time between occurrences of critical events (i.e., floods or drought events). An alternative definition of return period is the average number of trials required to the first occurrence of a critical event (e.g., Vogel, 1987; Bras, 1990; Douglas et al., 2002). Fernández and Salas (1999a) defined risk related to droughts as the probability that one or more droughts with duration (or magnitude) greater than or equal to a specified length (or magnitude) occurred during the project life. Another definition of return period has been the expected time interval between two

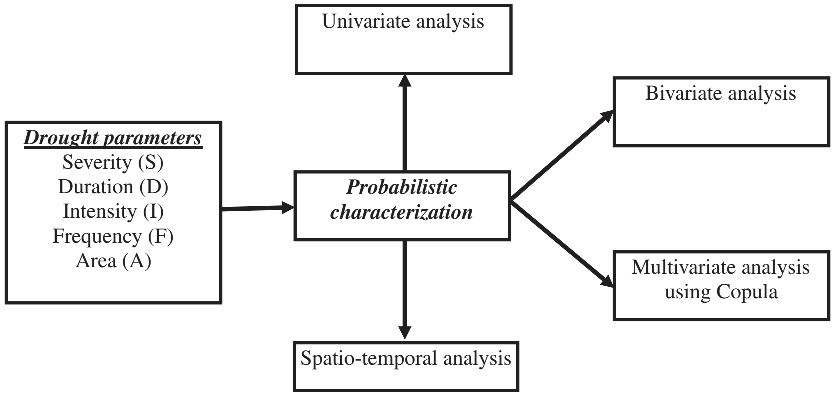


Fig. 4. Probabilistic characterization of drought parameters.

consecutive events or "interarrival time" or "recurrence interval" (Loaiciga and Marino, 1991). Frick et al. (1990) defined an n-year drought as the worst duration, severity, and magnitude drought that occurred in an n-year annual streamflow series. The interarrival time plays an important role in deriving the return period of a drought. In most of the existing approaches the dry and wet periods are modeled initially and their by-product gives rise to the drought interarrival time; however, Dupuis (2010) derived a new approach based on a combination of an empirical model and results from the extreme-value theory to achieve good fits over previous methods.

3.1.2. Return period analysis of drought events

In recent years several studies have been conducted to develop methodologies for estimating drought return periods (e.g., Fernández and Salas, 1999a,b; Chung and Salas, 2000; Kim et al., 2003). A common approach for characterizing droughts consists of fitting to sample data frequency distributions of drought characteristics (e.g., Sen, 1980a; Güven, 1983; Zelenhaśic and Salvai, 1987; Mathier et al., 1992; Sharma, 1995; Shiau and Shen, 2001). The probabilistic structure of droughts cannot be properly investigated, due to the limited number of drought events identified even in a long historical series. In order to overcome such a difficulty, the probabilistic behavior of drought characteristics has been generally derived analytically, assuming a given stochastic structure of the underlying hydrological series (e.g., Downer et al., 1967; Llamas and Siddiqui, 1969; Sen, 1976, 1977, 1980; Guven, 1983; Zelenhaśıc and Salvai, 1987; Mathier et al., 1992; Sharma, 1995; Shiau and Shen, 2001).

Some of the earlier applications of probability theory to drought parameters include the work by Downer et al. (1967) who analytically derived moments of run length and run sum under the hypothesis of independent and identically distributed (iid) random variables based on cumulant generating functions. Llamas and Siddiqui (1969) showed that under the iid hypothesis the probability distribution of run length was a geometric distribution. Sen (1976, 1977, 1980a,b) tried to use sequential periods (runs) as an analytical tool to solve the problem of deriving the probability distribution of drought characteristics and the important conclusions were: (i) the first-order linear autoregressive process and statistical properties of runs were functions of the first-order serial correlation coefficient, and (ii) as the serial correlation coefficient increased, the positive run length also increased, which may be interpreted as an increase in the long-term persistence measured by the Hurst coefficient.

Considering the underlying water supply variable as a first-order autoregressive model Millan and Yevjevich (1971) developed equations based on simulation studies to calculate the mean maximum drought length in a certain number of years. Gupta and Duckstein (1975) studied the distribution of the maximum run length assuming that the number of droughts in given time interval is Poisson distributed. A common approach for characterizing droughts consists of fitting the sample frequency distribution of drought characteristics using univariate probability distribution functions (e.g., Sen, 1980a,b; Güven, 1983; Zelenhaśic and Salvai, 1987; Mathier et al., 1992; Sharma, 1995; Shiau and Shen, 2001; Cancelliere and Salas, 2004).

Much of the reviewed literature reveals that the major emphasis in analyzing drought properties using analytical methods has been for cases where the underlying processes are stationary. Among the few studies available using periodic–stochastic processes is that by Fernandez and Vergara (1998), who used the algorithm proposed by Schwager (1983) to determine the return period of drought length for droughts starting in a given season, assuming a periodic Markov chain model. Cancelliere and Salas (2004) derived the probability mass function (pmf) of drought length and its first-order moments assuming a periodic Markov chain to estimate the probabilities of drought occurrence of a given length. It was observed that characterizing droughts using stochastic approaches and analytical derivations are useful for drought analysis. This is because the limited hydrologic records that are generally available do not allow observing many drought events of a particular duration and, in fact, extremely long droughts may not even be observable from the historical sample.

Shiau and Shen (2001) theoretically derived the return period of hydrological droughts with a severity greater than or equal to a fixed value, as a function of the expected value of drought interrival time and the cumulative distribution function of drought severity. Chang et al. (1984) developed a probability distribution of run length using the Discrete Autoregressive Average Process which related the drought to a run length of no precipitation. Salas et al. (2005) derived the severity of alternative drought events following a similar concept as the severity of floods. Chang (1990) defined the expected time between drought events using a Poisson distribution; whereas Nathan and McMahon (1990) evaluated the application of the Weibull distribution to low-flow frequency analysis. Fernandez and Vergara (1998) determined the return period of drought length for droughts starting in a given season assuming a periodic Markov chain model. Cebrian and Abaurrea (2006) derived the Poisson cluster process to represent drought occurrences and a marked process composed of three series of random variables (duration, deficit, and maximum intensity) to describe the drought severity. Gonzalez and Valdes (2004) derived the Mean Frequency of Recurrence (MFR) of droughts and discussed the main advantage of MFR calculation procedure over SPI. Srikanthan and McMahon (1985), Frevert et al. (1989) and Lana et al. (2006)

employed operational hydrology for drought frequency analysis based on marginal distribution functions to obtain information on dry periods. They investigated the generalized extreme value (GEV) and generalized Pareto (GP) distributions for modeling the series of annual extreme (AE) dry spells.

Drought frequency studies may be based on single site data (Yevjevich, 1967; Dracup et al., 1980a,b) or multisite data (Tase, 1976; Santos, 1983; Guttman et al., 1992; Soule, 1992), depending on the specific purpose of the study. In data scarcity situations it is important to use synthetic data for frequency studies (Shiau and Shen, 2001; Kim and Valdes, 2003; Karamouz et al., 2004; Mohan and Sahoo, 2007; Mishra et al., 2009). It is also important to test the type of probability distribution which fits the available data well, as the distribution is likely to vary, depending on the pattern of hydro-meteorological variables. For example, based on a 50 year time series of daily precipitation in a region of the middle Ebro valley (north eastern Spain) Serrano and Portugues (2003) showed that the generalized Pareto (GP) distribution combined with partial duration series (PDS) gave better results than did the Gumbel distribution. This demonstrates that the classical Gumbel approach underestimated the empirical duration of dry spells and that the distribution depends on hydro-climatic regions.

3.2. Bivariate drought analysis

A drought is a multivariate event characterized by its duration, magnitude, and intensity which are mutually correlated and therefore a better approach for describing drought characteristics is to derive the joint distribution of drought based on its characteristics. A bivariate distribution is thus more common and easier for describing the correlated hydrologic variables. Bivariate distributions have been commonly applied in drought analysis based on drought duration and severity (Shiau and Shen, 2001; Bonaccorso et al., 2003; Kim et al., 2003a; Gonźalez and Valdés, 2003; Salas et al., 2005; Mishra et al., 2009; Song and Singh, 2010a,b).

Formulating drought occurrences as an alternating renewal process (Fig. 5), which takes into account drought interarrival time expressions for the recurrence interval and the risk of occurrence, has been developed for droughts with different durations (Loaiciga and Leipnik, 1996; Fernández and Salas, 1999a,b), and different severities (Shiau and Shen, 2001). Gonźalez and Valdés (2003) developed a theoretical derivation of the return period of droughts being jointly characterized by durations and severities based on stochastic properties and run theory. Several methods have been proposed to investigate the bivariate characteristics of droughts. For example, Shiau and Shen (2001), Gonźalez and Valdés (2003), Salas et al. (2005), and Mishra et al. (2009) used the product of the conditional distribution of drought severity for a given drought duration and the marginal distribution of drought duration to construct the joint distribution of drought duration and severity. Kim et al. (2003a) used a nonparametric bivariate kernel estimator to establish the joint distribution of droughts. The simple Markov chain, usually adopted to model the sequence of deficits and surpluses, is not adequate when the underlying series exhibits a significant autocorrelation. Cancelliere and Salas (2010) derived the probability distribution of both drought duration and accumulated deficit (or intensity) as well as of the ensuing return period, when the underlying hydrological variable is autocorrelated.

One of drawbacks for these bivariate distributions is that the same family is needed for each marginal distribution. Namely, the above bivariate models cannot be applied to correlated hydrologic variables with marginal gamma and Gumbel distributions, which are frequently used in drought analysis. To overcome this problem copulas have been applied extensively in recent years which are discussed in the following section.

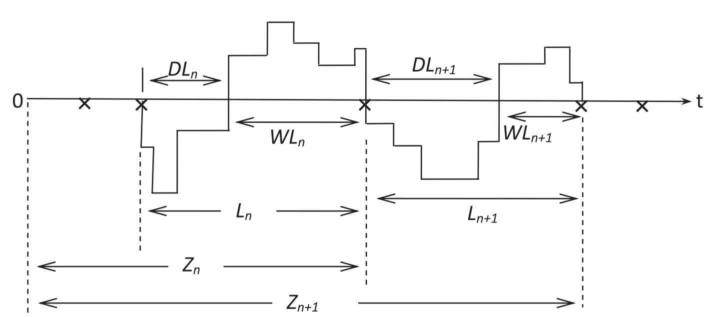
3.3. Multivariate drought characterization using copulas

Complex hydrologic events, such as droughts and floods, are multivariate events characterized by a few correlated random variables. Limited work has been done on the multivariate analysis of hydrologic events because of considerably more required data, sophisticated mathematical treatment, and the limited number of available models. In recent years, copula-based distributions are being increasingly employed in the field of hydrological engineering. Several illustrative and review studies (Favre et al., 2004; Salvadori and De Michele, 2004; Genest and Favre, 2007; Poulin et al., 2007; Zhang and Singh, 2006; 2007; Bárdossy and Li, 2008; Chowdhary and Singh, 2010) provide elaborate discussions on copula applications related to flow, rainfall and groundwater variables. Reference may be made to Joe (1997) and Nelsen (2006) for theoretical details on dependence and copulas. A brief overview of the copula concept is, however, given here to facilitate readers of its application for deriving joint distributions.

Considering a bivariate random variable (X, Y), its joint cumulative distribution function (cdf) $F(x, y)$, in terms of probability transformed or standard uniform variates $u = F_X(x)$ and $v = F_Y(y)$, is given as

$$F(x,y) = C_\theta[F_X(x), F_Y(y)] = C_\theta(u, v) \tag{4}$$

where $F_X(x)$ and $F_Y(y)$ are marginal cdfs, and C_θ: $[0,1] \times [0,1] \to [0,1]$, a mapping function, is the "copula" that combines marginal probabilities into joint probability. In turn, it means that a valid joint distribution model for (X, Y) is obtained, whenever the three



X = Initiation of a drought event DLn = Drought duration
WLn = Non drought duration Zn = Arrival time for nth drought event
Ln = Drought interarrival time between $(n+1)$ th drought and nth drought.

Fig. 5. Alternating renewal process.

constituents (C, F_X, and F_Y) are chosen from given parametric families, viz.,

$$F_X(x;\boldsymbol{\delta}), \quad F_Y(y;\boldsymbol{\eta}), \quad C_\theta(u,v;\boldsymbol{\theta}) \tag{5}$$

where $\boldsymbol{\delta}$ and $\boldsymbol{\eta}$ are the parameter vectors of marginal distributions, and $\boldsymbol{\theta}$ is the dependence parameter vector.

By double differentiating Eq. (4), the copula-based joint pdf, involving copula density $c_\theta(u,\ v)$ and marginal pdfs $f(x)$ and $f(y)$, is obtained as

$$f(x,y) = f(x)f(y)c_\theta(u,v) \tag{6}$$

There are several copula classes and families, such as Archimedean, meta-elliptic, extreme value, and miscellaneous. A number of models under each of these categories provide a great deal of flexibility in choosing copula models that may be suitable for any particular application. The functional forms of joint cdfs and pdfs of various copula models along with their dependence characteristics and parameter spaces are obtainable from any standard text on copula, such as Joe (1997) and Nelsen (2006). A conceptualization of a copula, adapted from Favre et al. (2004), is schematized in Fig. 6. Parameters of copula-based distributions are related to the nonparametric dependence measures, Spearman's rho and Kendall's tau, that represent the functional association among the random variables under consideration. Besides providing a remarkable flexibility of combining arbitrary marginals for deriving their joint distributions, the copula method offers a unique opportunity for its use in reducing uncertainty in estimates of frequency distribution parameters (Chowdhary and Singh, 2010).

Shiau (2006) modeled the joint drought duration (exponential distribution) and severity (gamma distribution) using two dimensional copulas using two separate maximum likelihood estimations of univariate marginal distributions followed by the maximization of bivariate likelihood as a function of dependence parameters. Shiau et al. (2007) investigated hydrological droughts of the Yellow River in northern China using a copula. Song and Singh (2010a) derived the joint probability distribution of drought duration, severity and interarrival time using a trivariate Plackett copula, where the drought duration and interarrival time each followed the Weibull distribution and the drought severity followed the gamma distribution based on streamflow data. Results showed that the Plackett copula was capable of yielding bivariate and trivariate probability distributions of correlated drought variables. Song and Singh (2010b) derived meta-elliptical copulas and Gumbel–Hougaard, Ali–Mikhail–Haq, Frank and Clayton copulas to determine the best-fit copula and observed meta-Gaussian and t copulas gave a better fit for multivariate drought characterization. Wong et al. (2010) investigated trivariate copulas of drought characteristics in Australia based on different climate states, El-Niño, Neutral, and La-Niña, according to the prevailing Southern Oscillation Index. This approach is quite useful as the marginal distributions of drought variables are different for different climate states.

Using the copula approach, Serinaldi et al. (2009) derived a four-dimensional joint distribution to model the stochastic structure of drought variables, and further drought return periods were computed as mean interarrival time, taking into account two drought characteristics at a time by means of the corresponding bivariate marginals of the fitted four-dimensional distribution. This methodology is suitable to jointly model drought characteristics and to compute exceedance probabilities of drought events. Application of copulas can be further explored for multivariate drought characterization based on both meteorological as well as hydrological variables to derive the joint information as meteorological droughts lead to hydrological droughts. Using the dependence structure of precipitation and streamflow marginals, Kao and Govindaraju (2010) derived a joint deficit index using the distribution function of copulas which could provide a probability-based description of the overall drought status.

4. Spatio-temporal drought analysis

The overall impact of a drought depends on several factors, severity, frequency, area, and duration which are essential for spatio-temporal analysis or in other words regional drought analysis (Mishra and Singh, 2009b). In a regional drought analysis, spatio-temporal patterns are investigated at different scales based on different thresholds and the region is classified based on different severity levels. Information on regional drought characteristics is critical and should be incorporated in strategic short as well as long-term water resource management. Therefore, one of the areas needing further research is the regional or spatial behavior of droughts (Rossi et al., 1992; Panu and Sharma, 2002). The frequency distribution of drought occurrence becomes more useful when it is quantitatively related to other aspects, such as drought severity, duration and area. This has led to the development of drought severity–area–frequency (SAF) curves, and severity–duration–frequency (SDF) curves and severity–area–duration (SAD) curves. These curves are useful for assessing droughts in a region.

Some of the earlier work based on spatio-temporal analysis of drought includes the work by Tase (1976) where he used a stochastic simulation approach with total areal deficit and maximum deficit intensity as primary drought indices to calculate the probability of areal coverage of drought and the probability of a specific region covered by the drought. Santos (1983) stochastically characterized multiyear regional droughts using probability distributions of drought duration, intensity and area. Alegria and Watkin (2007) characterized the spatial and temporal precipitation variability, drought frequency estimates and return periods of multiyear

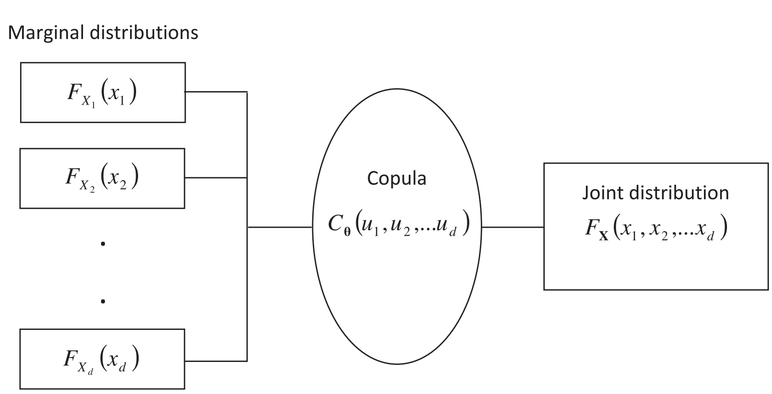


Fig. 6. Schematization of copula concept.

droughts using data to derive meteorological drought intensity–duration–frequency curves based on annual and warm season precipitation records. Using gridded precipitation and temperature data in a physically based macroscale hydrologic model at 1/2° spatial resolution over the continental United States, Andreadis et al. (2005) constructed drought history from 1920 to 2003 by deriving severity–area–duration (SAD) curves to relate the area of each drought to its severity.

Shin and Salas (2000) analyzed spatial and temporal patterns of meteorological droughts using a nonparametric spatial analysis neural network algorithm for constructing drought severity maps that displayed the spatial variability of drought severity for the whole region on a yearly basis. Hisdal and Tallaksen (2003) derived the probability of an area affected by a drought of a given severity and used it for calculating both meteorological and hydrological drought characteristics in Denmark. Further, the probability distribution functions of the drought covered area and the drought-deficit volume were derived and combined to produce drought severity–area–frequency curves.

Using drought indices like PDSI and SPI the spatio-temporal drought can be analyzed. For example, using PDSI as an indicator of drought severity in the Conchos River Basin in Mexico, Kim et al. (2002) developed a drought intensity–areal extent–frequency curve for the assessment of the severity of regional droughts. Mishra and Desai (2005b) and Mishra and Singh (2008) developed quantitative relationships between drought severity, area and frequency using SPI values for different time scales in Kansabati catchment, India. Using SPI, Vicente-Serrano (2006) analyzed differences in spatial patterns of droughts over a range of time scales. Using data from three Palmer indices [monthly moisture anomaly index (ZINX), drought severity index (PDSI), and hydrologic drought index (PHDI)] Soule (1992) examined patterns of drought frequency and duration in the contiguous United States based on multiple definitions of drought events.

Bewket and Conway (in press) analyzed rainfall variability both in terms of spatial and temporal scale, from decadal to daily time scales in the drought-prone Amhara region of Ethiopia. Sadeghipour and Dracup (1985) used a multivariate simulation model to determine exceedence probabilities of regional drought maxima from mean annual flow records of streams located in the San Joaquin Valley, California. Hisdal et al. (2001) analyzed a Pan-European dataset of more than 600 daily streamflow records from the European Water Archive (EWA) to detect spatial and temporal changes in hydrologic droughts. Shorthouse and Arnell (1997), Tallaksen et al. (1997), Adler et al. (1999), and Stahl and Demuth (1999) have shown that meteorological and hydrological droughts at regional scales are determined by large-scale atmospheric circulation anomalies. Clausen and Pearson (1995) investigated the spatial and temporal variability of droughts by a regional frequency analysis of annual minimum stream flows. Lana and Burgue~no (1998) characterized spatial and temporal extreme droughts in northeast Spain. A high spatial resolution, multi-temporal climatology for the incidence of 20th century European drought was presented by Hughes and Saunders (2002). However, large-scale atmospheric circulation patterns affect regional droughts in terms of spatial and temporal variations and little work in this area has been done so far. Application of general climate models in recent decades has made it possible to study the changes in drought characteristics, which is discussed in the following section.

5. Drought modeling under climate change scenarios

Global surface temperature has increased significantly during the last century and will continue to rise unless greenhouse gas emissions are drastically reduced (IPCC, 2007). The effects of climate change are diverse and vary regionally, even locally, in their intensity, duration and areal extent. To understand the impact of climate change Global Climate Models (GCMs) outputs are downscaled to model drought variables at a local scale.

Future drought scenarios can be investigated based on the precipitation anomalies derived from GCM models. For example, Blenkinsop and Fowler (2007) derived a simple drought index based on monthly precipitation anomalies from six regional climate models (RCMs) for six catchments across Europe. Interesting observations were made with the increase in the frequency of long-duration droughts for catchments in southern Europe, and less frequent droughts for a catchment in northern England, though considerable variation in model skill in reproducing monthly mean precipitation was observed. In another study, Wang (2005) analyzed the change in precipitation and soil moisture content in response to the rising GHG concentrations based on 15 Global Climate Models. The observations included: the models were consistent in predicting summer dryness and winter wetness in only parts of the northern middle and high latitudes. Several studies using climate models have suggested that the interior of the northern hemisphere continents will become drier over the next century, especially in summer (Rind et al., 1990 and Wetherald and Manabe, 2002).

Climate change affects the global hydrologic cycle which leads to spatio-temporal variability of precipitation at different scales. Therefore, based on precipitation using SPI as drought indices it will be useful to study future drought scenarios using GCM models. Loukas et al. (2007) evaluated various climate change scenarios for understanding drought characteristics in the regions of Greece using SPI and highlighted the increase in drought severity, intensity and duration based on different future scenarios with respect to historical droughts. Ghosh and Mujumdar (2007) investigated the uncertainty due to different GCM projections and also incorporated it for examining future drought scenarios. Loukas et al. (2008) used outputs of CGCMa2 and two socioeconomic scenarios, namely, SRES A2 and SRES B2 for the assessment of climate change impact on droughts in Greece and observed that the annual drought severity increased for all hydrological areas and SPI time scales, with the socioeconomic scenario SRES A2 being the most extreme. Future drought scenarios can be investigated based on the precipitation anomalies derived from GCM models. For example, Blenkinsop and Fowler (2007) derived a simple drought index based on monthly precipitation anomalies from six regional climate models (RCMs) for six catchments across Europe. Interesting observations were made with the increase in the frequency of long-duration droughts for catchments in southern Europe, and less frequent droughts for a catchment in northern England, though considerable variation in model skill in reproducing monthly mean precipitation was observed.

In another study, Mishra and Singh (2009b) derived an approach as shown in Fig. 7 to investigate the impact of climate change on severity–area–frequency (SAF) curves for annual droughts in the Kansabati River basin, India, and compared with historical droughts in the basin. The overall methodology for construction of SAF curves consisted of two parts: (i) downscaling of precipitation at grid levels which included identification of GCMs, selecting predictors, downscaling using suitable techniques, bias correction and interpolating precipitation at fine grids and (ii) development of SAF curves based on downscaled precipitation by deriving drought properties, identifying a suitable probability distribution, and performing frequency analysis at different return periods. Results showed that there were likely to be more severe droughts in 2001–2050 with more spatial extent than those that have occurred historically.

Understanding drought as a result of variability in precipitation, temperature and soil moisture, PDSI can be used to assess future

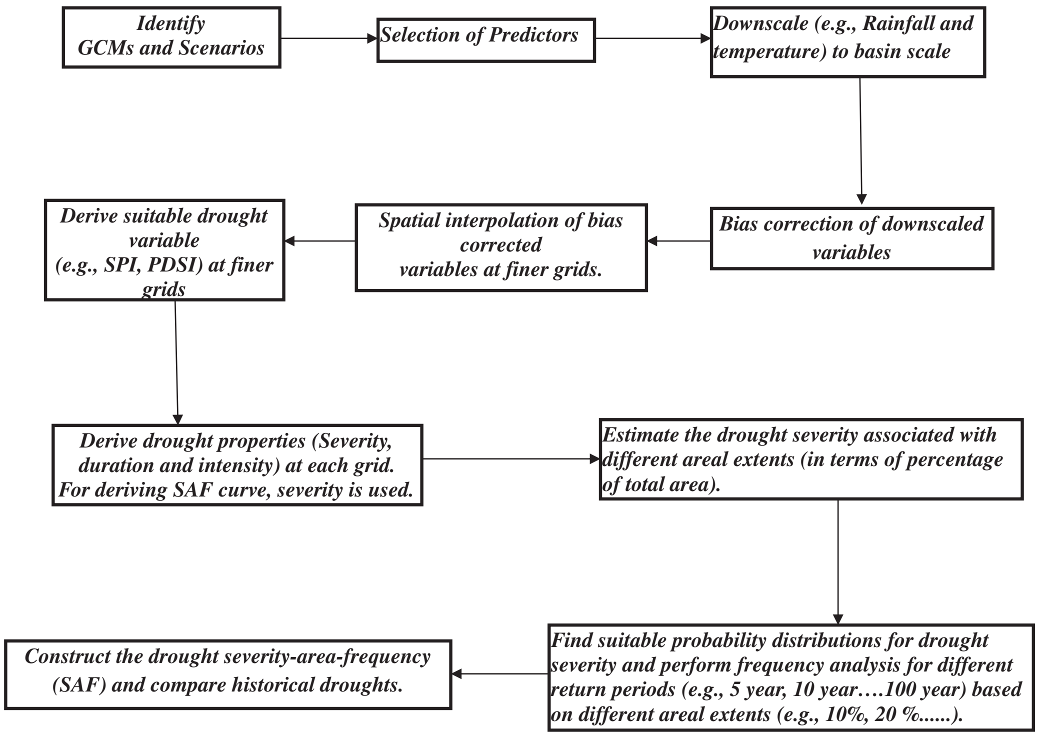


Fig. 7. Methodology for constructing drought SAF curves based on GCM outputs.

drought scenarios using GCM models. Burke et al. (2006) calculated PDSI, using the Hadley centre climate model for the SRES A2 scenario, and found a net global drying trend resulting in an increase in the area of an extreme drought from 1% to 30% by the end of this century. Kothavala (1999) applied PDSI to a coupled ocean atmosphere GCM with a transient increase in CO_2 to grid points over Australia and results indicated El Niño-like conditions were likely to cause a considerable increase in the duration and severity of drought in the region. Dubrovsky et al. (2009) made an interesting observation in comparing SPI and PDSI for understanding climate change impacts on drought scenarios using GCM outputs and concluded that the drought changes indicated by SPI-12 followed the projected annual precipitation changes, whereas the change in the PDSI was influenced by both precipitation and temperature under all climate change scenarios as it was expected according to PDSI computation. Because of the dependence of drought on temperature and precipitation, PDSI is more appropriate in comparison to SPI for use in assessing the potential impact of climate change on future droughts.

Based on the output from the Hadley Centre regional climate model (HadRM3) and using the standardized 12-month precipitation accumulation as a drought matrix, Burke and Brown (2010) characterized regional droughts and projections of changes in drought characteristics over the second half of the 21st century under increased atmospheric greenhouse gases hinted at an increase in the severity of drought. Climate variability affects the pattern of precipitation, evaporation and temperature which ultimately affects the crop production in a region, hence using GCM and drought indices the future crop prediction can be evaluated. In a study Mavromatis (2007) evaluated SPI and three variations of the Palmer Drought Severity Index (PDSI) for assessing future wheat production in Greece using the Hadley Centre regional climate model HadRM3.

However, the utility of GCMs is limited by unrealistic time structure of daily rainfall and biases in rainfall frequency and intensity distributions, which has been an obstacle for dry spell analysis. Several ways have recently been developed for improving the daily structure of GCM rainfall, for example, using bias correction-stochastic disaggregation methods (Ines et al., in press) which can be explored further to improve dry spell analysis. Due to the deficiencies as well as uncertainties, an individual Global Climate Model is likely to adversely affect the analysis of future drought scenarios, therefore their uncertainties must be adequately characterized to provide credible guidance to adaptation strategies. Therefore, uncertainties arising from the actual modeling of the physical climate and natural variability can be characterized through the use of model ensembles (Burke and Brown, 2010). For a full discussion on downscaling capabilities, limitations, uncertainties and existing gaps from GCMs simulations the reader is refer Maraun et al. (2010).

5.1. Application of large-scale hydrology models for climate change scenarios

Several studies used a large-scale hydrology model to simulate land surface water and energy fluxes from the scale of large watersheds to global simulations for understanding future drought characteristics under climate change scenarios. For example, using a Variable Infiltration Capacity (VIC) model, soil moisture and runoff have been widely used to study retrospective droughts (Andreadis et al., 2005; Andreadis and Lettenmaier, 2006; Mo, 2008; Shukla and Wood, 2008; Mishra et al., 2010). Some of the studies based on future climate scenarios include the work by Sheffield and Wood (2008) who investigated changes in drought occurrences using soil moisture data from eight AOGCMs that participated in the IPCC AR4. Interesting conclusions were drawn: regionally, the Mediterranean, West African, Central Asian and Central American regions showed large increases most notably for long-term frequencies as did mid-latitude North. Increases of droughts are driven primarily by reductions in precipitation with increased evaporation from higher temperatures modulating changes. Mishra et al. (2010) investigated the regional scale (Illinois and

Indiana) droughts using the Variable Infiltration Capacity (VIC) model and examined associated severity, areal extent, and temporal extent under historic and projected future climate scenarios and observed that the study region was experiencing reduced extreme and exceptional droughts with lesser areal extent in recent decades.

6. Application of land data assimilation system for drought modeling

There has been a reduction in hydrometric stations around the world in recent decades (Mishra and Coulibaly, 2009) which affects drought monitoring at finer spatial scales, therefore remote sensing approach plays an important role for drought monitoring. Remote sensing proves to be quite useful in the decision making process for identifying areas undergoing exceptional droughts (McVicar and Jupp, 1998).

Several studies identified that application of satellite observations can improve the accuracy and spatial detail in hydrological model estimation as all operational systems use, dynamic forcing, land cover classification and a priori parameterisation of vegetation dynamics that are partially or wholly derived from remote sensing (van Dijk and Renzullo, 2011). As real-time drought monitoring is based on reliable estimation of spatial and temporal variation of soil moisture, the greater use of remote sensing data is desirable for model evaluation and data assimilation. Sometimes, satellite observations alone are not sufficient for measurement of soil moisture (Moradkhani, 2008) for: (i) temporal and spatial gaps in their coverage and (ii) deeper soil moisture cannot be observed directly from space. Therefore, the best possible system would integrate the benefits of land surface models and in situ and satellite observations to assess global soil moisture conditions through data assimilation to improve upon the accuracy of estimation (Moradkhani, 2008).

Data assimilation is a way to integrate data from a variety of sources with different resolutions and accuracies and research has gained significant momentum in the last two decades. Several studies demonstrated the potential of data assimilation to improve the land surface model predictions (Reichle et al., 2002, 2007; Margulis et al., 2002) based on the combination of data from multiple sources within models to produce gridded land surface fluxes. During recent decades large efforts have been devoted to create estimates of soil moisture fields using the North America Land Data Assimilation System (NLDAS) (Mitchell et al., 2004) and the Global Land Data Assimilation System (GLDAS) (Rodell et al., 2004) (http://ldas.gsfc.nasa.gov/). The goal of NLDAS is to construct quality-controlled, and spatially and temporally consistent, land surface model (LSM) datasets from the best available observations and model output to support modeling activities. For details of the land data assimilation system the reader can refer to NASA website (http://ldas.gsfc.nasa.gov/index.php). The NLDAS experimental drought monitor is derived from near real-time soil moisture output from a combination of models (NASA MOSAIC and NCEP Noah land surface models) and output is available with 5-day latency, and soil moisture percentile (http://www.emc.ncep.noaa.gov/mmb/nldas/drought/).

The soil moisture values obtained based on the realtime NLDAS forcing have shown to accurately represent soil moisture dynamics (Maurer et al., 2002; Robock et al., 2003; Luo and Wood, 2008). The soil moisture time series can be further explored using different threshold levels or percentiles using the theory of runs to quantify droughts as well as to forecast droughts at different lead times (Mishra and Singh, 2010). Using the real-time atmospheric forcing provided by NLDAS in the land surface Variable Infiltration Capacity (VIC) land surface model, Luo and Wood (2007) developed a drought monitoring and prediction system which is capable of providing a quantitative assessment of droughts in near real-time. However it is worth noting that the potential of drought monitoring differs, based on climatic patterns, for example the model was able to predict the onset of the current severe drought over the western part of USA with great confidence, whereas in the southeast part of USA the confidence was lower.

7. Drought management

Even though there is a significant improvement in weather forecasting, the costs resulting from disasters around the world are still high and rising, indicating growing societal vulnerability to natural hazards (Changnon et al., 2000; Wilhite, 2000a; Bender, 2002). With increasing scarcity of drinking water due to rapidly growing populations, economies and hydro-meteorological variability, there is always a daunting task in managing water resources during periods of droughts as observed during past decades (e.g., Hirsch, 1981; Frick et al., 1990; Randall et al., 1990; Johnson and Kohne, 1995; Smithers, 1997). To overcome the challenges due to increased drought recurrences and to reduce impacts there is a need for long term focus and therefore to develop effective strategies for drought management to maintain water security. Based on experiences of droughts, the National Drought Mitigation Center (NDMC, USA) suggests that one way to identify appropriate drought mitigation actions is to conduct an overall risk analysis as part of drought planning (Wilhite, 2000a,b). Therefore, to understand drought risk, it is important to understand natural hazards and develop a practical, action-oriented model to assist drought planners on a variety of political and geographic scales (Hayes et al., 2004).

7.1. Factors affecting drought management

The effective drought management depends mainly on two input factors: (a) impacts of natural triggered hydro-meteorological variability on water resources systems and (b) utilizing the information obtained from modeling different drought components qualitatively for planning. However, understanding natural triggered variability in hydro-meteorological parameters is complex, therefore extracting useful information from modeling different drought components as discussed in the previous sections is crucial for mitigating droughts. For example, higher variability in hydro-meteorological variables increases the uncertainty in deriving drought forecasting models for early warning systems, which also is applicable in modeling other drought components. The following section discusses essential aspects for drought management which include decision support system (DSS) approaches and multi-criteria decision analysis.

7.2. Expert system/decision support system (DSS) approach

The use of expert systems in water resource applications has been a difficult problem mainly due to the stochastic characteristics of water resources (Quinlan, 1987), however recent advances in computer technology and improved hydrologic and hydraulic modeling approaches, and availability of high quality real-time hydrometric data have led to user-friendly graphical model interfaces for developing decision support systems (DSSs) for water resource systems. A DSS is based on integration of individual models, for example, a DSS for reservoir operation under drought scenario can be a combination of several models, as shown in Fig. 8. Here the user input consists of precipitation, reservoir inflow, historical water demand, historical drought scenarios and corresponding water levels. The user's knowledge of model development includes rainfall and runoff modeling for reservoir inflow forecasting, opti-

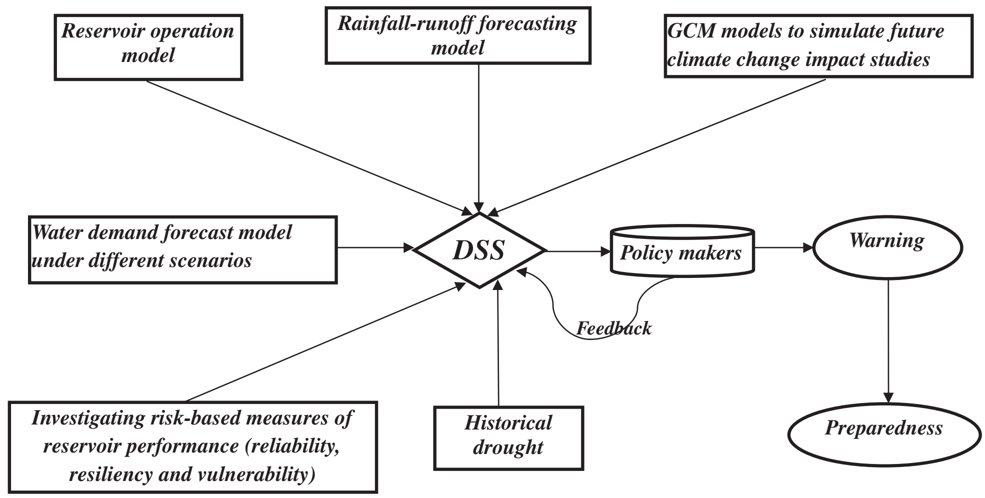


Fig. 8. DSS for reservoir operation in drought management scenario.

mization procedures for reservoir operation by allocating water demands based on user's need, appropriate models for water demand forecasting, derivation of methodologies for quantifying the impact of climate change on reservoir operation and characterization of historical droughts using suitable models. The outputs obtained from the DSS include: (i) the reservoir capacity based on different scenarios and comparison of current demands as well as those based on future drought scenarios; (ii) multivatiate drought characterization considering different drought parameters, for example, reservoir deficit and its duration, etc.; and (iii) investigating risk-based measures of reservoir performance based on reliability, resiliency and vulnerability under different drought scenarios. These outputs from DSS are passed onto the policy maker to evaluate several questions whether the output obtained matches real-time operation and their feedback is important for better performance of DSS. Finally the policy maker issues warning as well as suggests preparedness action plans.

With the rapid development of information technology, DSSs are considered the best, practical tools for integrated water resources management (Jamieson and Fedra, 1996; Simonovic and Bender, 1996), however, to date only a few DSSs have been developed to consider the issue of drought management. Palmer and Holmes (1988) developed an integrated drought management expert system for the Seattle Water Department, Washington, USA, and the knowledge base of their expert system was rule based. Chang et al. (1996) developed a daily drought monitoring system using the working memory which contains facts of historial drought characteristics, including truncation levels, mean durations, and mean conditional probabilities estimated at gauging stations. Walker et al. (1993) described the Drought Watch Decision Support System based on data for the current reservoir levels and starting month to simulate monthly storage patterns under different cumulative runoff conditions, having specified exceedence probabilities. Their risk analysis model estimates the likelihood of failure, and predicts the month in which such a failure will occur for the drought management of North West Water, UK. Merabtene et al. (2002) developed a decision support system (DSS) to assess the susceptibility of water supply systems to droughts, and to aid decision-makers in determining optimal supply to the water resources system in Fukuoka City, western Japan. Pallottino et al. (2005) developed a DSS that performed scenario analysis by examining a set of statistically independent hydrological scenarios based on their temporal evolution and identifying trends and essential features on which to base a robust decision policy.

7.3. Multi-criteria decision analysis

Multi-criteria decision analysis (MCDA) aims at helping a decision maker to prepare and make a decision where more than one point of view has to be considered, which enables decision makers to obtain a better understanding of the available choices, providing information about the trade-offs among different alternatives (Figueira et al., 2005). Drought management is a multidimensional concept, including meteorological, ecological, hydrological, environmental, and socio-economic perspectives. When it comes to making decisions on drought management, human intervention, based on the need of stakeholders often makes decision making difficult. Therefore, it is advisable to resolve these decision problems based on scientific decision using MCDA.

Several applications of MCDA are also oriented to assist the decision making process in the operation of water systems. For example, Duckstein (1983) proposed a methodology based on several combinations of supply-oriented, demand-oriented, and impact minimization oriented measures, and their consequences were assessed in terms of economic, hydrologic (water deficits), social, and environmental criteria. A comparative assessment of drought mitigation measures using application of MCDA was carried out by Rossi et al. (2005) for drought management by evaluating drought vulnerability of water supply systems and assessing different courses of action considering economic, environmental, and social criteria. Traore and Fontane (2007) described an approach for drought management, based on MCDA model using different measures, which include: strategic long term measures for combating any drought, tactical intermediate term measures based on single drought event and emergency for short term measures. Palmer and Tull (1987) developed an expert system to select appropriate response measures by comparing existing conditions with a variety of historical drought scenarios stored in a database. However, a major problem in developing MCDA is to understand drought risks associated with persistent drought conditions, as risk management involves inherently subjective considerations; also it is difficult to translate risk into publically acceptable terms (Westphal et al., 2007).

8. Conclusions

It is anticipated that the future will witness increased dynamics in hydro-meteorological variables around the world which will lead to frequent droughts whose impacts will be compounded by growing water demands. Although significant progress has been achieved in drought modeling, much work remains ahead. This contribution provides a review of the methods used for modeling different components of droughts, which will be useful for different sectors dealing with water resources directly or indirectly. The following conclusions are drawn from the foregoing review:

1. The changing pattern of teleconnections in terms of spatial and temporal scales complicates long range drought forecasting. To reduce the uncertainty due to changing patterns of climate change as well as to improve long range forecasting, more research is needed to understand the dynamics associated with multiple climatological, oceanic, meteorological, and hydrological parameters as well as local factors like regional water demand. Use of data mining will be highly useful for exploring the changes and to identify suitable predictors at different spatio-temporal scales. It is possible to explore the periodic nature of hydro-climatic variables to forecast droughts on decadal scales, though this line of work was widely used in the 1970s, based on recent developments in pattern recognition techniques, the advancement in long-term drought forecasting needs to be further explored. Even though many forecasting methods are based on the assumption of stationarity, however, based on empirical evidence temporal variability in trends, oscillatory behavior, and sudden shifts are commonly observed. Therefore, a probabilistic framework for modeling the temporal dynamics of time series will be one of the important components likely to have more potential to capture the dynamics of abrupt shifts in drought patterns. For longterm forecasting (years to decade) different climate forcing scenarios can be explored using coupled GCMs.
2. A drought is a multivariate event. Therefore, a better approach for describing drought characteristics is to derive the joint distribution of a drought based on its characteristics. The limitations in earlier approaches for deriving joint probability distributions are based on the sameness of marginal distribution for each drought variable. However, recent developments in the application of copulas offer a great deal of flexibility for multivariate drought characterization. However, the type of copulas differs, based on the characteristics of time series. Therefore, identifying a suitable copula will be required for multivariate drought characterization. The copula method can be further explored to characterize droughts based on the combination of different types of droughts for extracting better information with respect to different return periods. This combined approach can be a combination of the meteorological, agricultural and hydrological droughts for multivariate drought characterizations. There is also a possibility for deriving different drought indices based on multiple types of droughts.
3. Spatio-temporal drought analysis based on the combination of duration, severity, area and interarrival time are critical for short and long-term water management. There is much work done on this aspect, however the gauged data used on spatial scale are unable to produce accurate results due to missing values as well as large distances between gauging stations. Therefore the availability of remote sensing data will play a crucial role in overcoming these problems. Hence, regionalization of droughts based on remote sensing data needs to be explored. The linkage between large-scale atmospheric patterns and regional droughts can be another way for exploring spate-time variability of droughts from local to regional scale, which needs to be investigated as future work. So far the regionalization of droughts is based on hydro-meteorological variables, however the major factor affecting droughts is growing water demand with limited natural source of water supply, hence there is scope for regionalization of droughts based on the spatial and temporal water demands.
4. Climate change will affect water resources in the future due the changes in hydro-meteorological variables at different scales. Therefore, the future drought scenarios of a region can be investigated based on continuing developments in the accuracy of GCM and RCM's output. However, much scope remains in reducing the uncertainty while using GCM outputs for modeling different drought variables. Another observation suggests that GCM's are able to model temperature variability with lesser uncertainty in comparison to precipitation. Therefore, drought indices that depend on both precipitation and temperature instead of only precipitation will be more suitable for climate change scenario studies for drought modeling. For example, using GCM outputs, the modeled drought properties changes indicated by an SPI series will demonstrate higher uncertainty, as it depends solely on precipitation in comparison to PDSI as it is influenced by both precipitation and temperature. Also, advancements occurring in large-scale hydrologic modeling to simulate energy fluxes from the scale of large watersheds to global simulations will be useful for drought characterization under climate change scenarios.
5. The development of data assimilation based on the integration of data from a variety of sources with different resolutions demonstrates the potential to improve land surface model predictions. Therefore, there is a long way to go for real-time drought prediction in many countries, and care is to be taken in the development of a land data assimilation model as differences in climatic patterns affect real-time drought prediction.
6. Even though substantial work has been done on different aspects of droughts, a proper approach to convey the results of research to decision makers is not as well articulated. There is a need to develop decision support systems (DSS) under climate change scenarios as well to quantify uncertainties for issuing warnings, assessing risk, and taking precautionary measures.

This study has examined a number of literature sources; however it seems to be virtually impossible to include in a review all publications. This review paper highlights an overall approach for drought modeling and each section deserves a more comprehensive, special review. It is expected that these gaps could be filled by subsequent contributions and that there is scope for further discussion about drought research possibly in the broader context of future development of the entire hydrological science.

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