Journal of Hydrology 512 (2014) 134–146

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Spatio-temporal drought forecasting within Bayesian networks

Shahrbanou Madadgar, Hamid Moradkhani *

Department of Civil and Environmental Engineering, Portland State University, Portland, OR 97201, USA

ARTICLE INFO

Article history:
Received 4 September 2013
Received in revised form 6 January 2014
Accepted 15 February 2014
Available online 5 March 2014
This manuscript was handled by Konstantine P. Georgakakos, Editor-in-Chief, with the assistance of Ashish Sharma, Associate Editor

Keywords:
Drought forecast
Standardized Runoff Index
Bayesian networks
Copula
Conditional probability

SUMMARY

Spatial variations of future droughts across the Gunnison River Basin in CO, USA, are evaluated in this study, using a recently developed probabilistic forecast model. The Standardized Runoff Index (SRI) is employed to analyze drought status across the spatial extent of the basin. The runoff generated at each spatial unit of the basin is estimated by a distributed-parameter and physically-based hydrologic model. Using the historical runoff at each spatial unit, a statistical forecast model is developed within Bayesian networks. The forecast model applies a family of multivariate distribution functions to forecast future drought conditions given the drought status in the past. Given the runoff in the past (January–June), the forecast model is applied in estimating the runoff across the basin in the forecast period (July–December). The main advantage of the forecast model is its probabilistic features in analyzing future droughts. It develops conditional probabilities of a given forecast variable, and returns the highest probable forecast along with an assessment of the uncertainty around that value. Bayesian networks can also estimate the probability of future droughts with different severities, given the drought status of the predictor period. Moreover, the model can be used to generate maps showing the runoff variation over the basin with the particular chance of occurrence in the future. Our results indicate that the statistical method applied in this study is a useful procedure in probabilistic forecast of future droughts given the spatio-temporal characteristics of droughts in the past. The techniques presented in this manuscript are suitable for probabilistic drought forecasting and have potential to improve drought characterization in different applications.

1. Introduction

The National Oceanic and Atmospheric Administration's (NOAA, 2013) National Climate Data Center reported the year 2012 as the warmest year on record for the United States. Over the entire year of 2012, average temperatures of the contiguous United States were 3.2 °F above that of the 20th century. According to the U.S. Drought Monitor, more than 70% of the contiguous United States experienced some level of dry spells being classified from abnormal to exceptional droughts in 2012. The droughts of 2012 extended to the next year and approximately 58% of the contiguous United States was under drought conditions as of January 29, 2013. Many major rivers in the Western U.S., including the Colorado and the Rio Grande, had below average streamflow in the spring and summer of 2013. The ongoing droughts in the North America and many other regions across the globe are referred to the climate change and global warming effects (Trenberth, 2011; Peterson et al., 2012) and the frequency of future droughts is expected to be increasing, rather than decreasing (Sheffield and Wood, 2008; Dai, 2011). Consequently, a reliable hydrologic forecast for a region has a significant role in the efficient planning of available water resources.

Droughts have strong impacts on the water supply and quality; society and public health; crop production and agriculture; plants, wild fires, and living environments. A variety of studies in the past decades have examined the different aspects of drought events, such as developing different drought indicators (Niemeyer, 2008; Mishra and Singh, 2010), monitoring and characterizing the droughts (Andreadis and Lettenmaier, 2006; Shukla et al., 2011; Shiau, 2006; Dupuis, 2007), climate change impacts on future droughts (Ghosh and Mujumdar, 2007; Sheffield and Wood, 2008; Burke et al., 2010; Moradkhani et al., 2010; Risley et al., 2011; Madadgar and Moradkhani, 2011), and developing early warning systems to survive in drought conditions (Huang and Chou, 2008). There are also a number of studies focused on drought forecasting and estimating the likely drought conditions in the future. In an earlier study, Karl et al. (1987) evaluated the probability of receiving a sufficient amount of precipitation to recover from an ongoing drought over a particular period of time. They rewrote the

* Corresponding author. Address: 1930 SW 4th Avenue, Suite 200, Portland, OR 97201, USA. Tel.: +1 503 725 2436.

E-mail addresses: madadgar@pdx.edu (S. Madadgar), hamidm@pdx.edu (H. Moradkhani).

http://dx.doi.org/10.1016/j.jhydrol.2014.02.039
0022-1694/© 2014 Published by Elsevier B.V.

Palmer Drought Severity Index (PDSI; Palmer, 1965) and utilized the unconditional gamma distribution to obtain the probabilities of future droughts. However, this is disputed for ignoring the dependency and auto-correlation in a precipitation record. Since then, several other methods have been developed and tested in drought forecasting such as Markov Chain model (Lohani and Loganathan, 1997; Steinemann, 2003), stochastic renewal models (Kendall and Dracup, 1992; Loaiciga and Leipnik, 1996), stochastic autoregressive models (Mishra and Desai, 2005), and artificial neural networks (Mishra and Desai, 2006; Barros and Bowden, 2008). Cancelliere et al. (2007) discussed the validity of Markov Chain model for making significant errors in transition probabilities of the Standardized Precipitation Index (SPI; McKee et al., 1993) and then derived the transition probability matrix by an analytical study on the statistics underlying the SPI equations. However, Madadgar and Moradkhani (2013) recently argued, in an analytical framework, that the assumption of independent and normally distributed aggregated precipitation volumes is not always true, especially for other hydrologic variables such as runoff and streamflow. They also discussed that for frequency analysis of different drought states, the intense process of obtaining the transition probability matrix from the index equation could be avoided by using multivariate modeling based on copula functions (Joe, 1997). In several other studies, the climate forecast products of NOAA Climate Prediction Center (CPC) are used for developing probabilistic drought forecasts (Carbone and Dow, 2005; Hwang and Carbone, 2009). However, Steinemann (2006) discussed the poor interpretation of forecast probability and uncertainty information supported by CPC forecast products in real applications.

This study extends the application of the recently developed model in drought forecasting by Madadgar and Moradkhani (2013). In the previous application, the forecast model predicted the future droughts of the Gunnison River Basin (GRB) in Colorado, USA, using the flow volume at the basin outlet. The promising results of that study have encouraged the authors to apply their forecast model in estimating the spatial variation of future droughts using the runoff volume at different grid cells across the basin. Copulas (Joe, 1997; Nelsen, 1999), as the main core of the proposed forecast model, are multivariate distribution functions that join the marginal distributions of the variables with some level of dependency and correlation. According to the existent correlations among the hydrologic variables like runoff, streamflow, groundwater level, and many other variables, the copula functions have been examined in different hydrologic applications over the past few years (e.g. Favre et al., 2004; Bárdossy, 2006; Shiau, 2006; Dupuis, 2007; Zhang and Singh, 2007; Salvadori and De Michele, 2010; Kao and Govindaraju, 2008, 2010; Madadgar and Moradkhani, 2011; Madadgar et al., 2012). In drought applications, copulas have been used to characterize the future droughts in terms of estimating the return period of droughts' severity, intensity, and duration, (Shiau, 2006; Dupuis, 2007; Kao and Govindaraju, 2010; Wong et al., 2010; Madadgar and Moradkhani, 2011). However, in a recent study by Madadgar and Moradkhani (2013), a new application of copula functions in drought forecasting was examined, where instead of analyzing the drought characteristics; they studied the occurrence probability of seasonal droughts regarding streamflow observations. They defined the conditional probability of streamflow via Bayesian networks. According to the correlations among the streamflow of consecutive seasons, the conditional probabilities of seasonal droughts were analyzed using the copula functions adopted in a Bayesian framework. This study aims at extending the application of the proposed copula-based method to estimate the spatial variation of future drought probabilities across the GRB. For this purpose, the runoff generated across the basin is used to evaluate the spatial variation of droughts; while in the previous study, the streamflow observations at a particular point were used for drought forecasting.

The paper is organized as follows. Section 2 explains the drought index to evaluate droughts based on the runoff volume at each spatial unit across the basin. Section 3 describes the hydrologic modeling of GRB and analyzes the historical droughts of the basin. Section 4 elaborates on the probabilistic forecast methodology employed in this study, and is followed by a discussion on the required analyses to apply the forecast model (Section 5). Section 6 demonstrates some forecast products for the study basin and discusses the results. Finally, Section 7 summarizes the major remarks of the study.

2. Standardized Runoff Index (SRI)

Standardized Runoff Index (SRI; Shukla and Wood, 2008) is used to evaluate the spatial variation of the hydrologic drought across the study area. As with all Standardized Indices (SI), the SRI of each spatial unit reflects the anomalies of surface runoff from its average value generated in the same unit. Mathematically, SRI is defined as the standardized normal variable of the accumulated surface runoff over a specific time period:

$$\begin{aligned} SRI^s_{yr,m,k} &= \phi^{-1}(u^s_{yr,m,k}) \\ u^s_{yr,m,k} &= F_{X^s_{yr,m,k}}(X^s_{yr,m,k}) \\ X^s_{yr,m,k} &= \sum_{i=m}^{m+k-1} y^s_{yr,i} \end{aligned} \tag{1}$$

where $u^s_{yr,m,k}$ is the probability of the total runoff volume at the spatial unit s in year yr over k months starting from month m; $F_{(\cdot)}$ is the marginal distribution of accumulated runoff ($X^s_{yr,m,k}$); and $y^s_{(\cdot)}$ is the monthly runoff of the spatial unit s. Therefore, the SRI calculation starts with fitting an appropriate marginal distribution to the total runoff volume over k months and computing the standardized normal variable for each aggregated runoff volume. According to Eq. (1), separate marginal distributions should be fitted to the accumulated runoff beginning from different months to obtain the SRI variation over time for each spatial unit. As explained by Madadgar and Moradkhani (2013), Eq. (1) can preserve the natural periodicity (seasonality) of surface runoff, where the runoff variation among the low-flow and high-flow seasons is appropriately reflected in the definition of SRI.

Once the SRI is estimated for each spatial unit, the drought status of each unit can be determined by the U.S. Drought Monitor classification for the standardized drought indices (Table 1). Using this classification, one out of five drought categories can be recognized for a region at any time. The SRI = −0.5 separates the dry periods from the wet periods, while the variation in water availability during a time horizon results in a dynamic transition either between dry and wet spells, or among various drought categories.

Table 1
Drought classification by the U.S. Drought Monitor (http://droughtmonitor.unl.edu/) for the Standardized Indices (SI).

Drought category	Drought severity	SI value
D0	Abnormally dry	−0.5 to −0.7
D1	Moderate drought	−0.8 to −1.2
D2	Severe drought	−1.3 to −1.5
D3	Extreme drought	−1.6 to −1.9
D4	Exceptional drought	−2.0 or less