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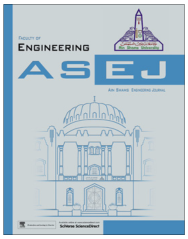

CIVIL ENGINEERING

Forecasting of meteorological drought using Hidden Markov Model (case study: The upper Blue Nile river basin, Ethiopia)

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Abstract An improved drought management must rely on an accurate monitoring and forecasting of the phenomenon in order to activate appropriate mitigation measures. In this study, several homogenous Hidden Markov Models (HMMs) were developed to forecast droughts using the Standardized Precipitation Index, SPI, at short-medium term. Validation of the developed models was carried out with reference to precipitation series observed in 22 stations located in the upper Blue Nile river basin. The performance of the HMM was measured using various forecast skill criteria. Results indicate that Hidden Markov Model provides a fairly good agreement between observed and forecasted values in terms of the SPI time series on various lead time. Results seem to confirm the reliability of the proposed models to discriminate between events and non-events relatively well, thus suggesting the suitability of the proposed procedure as a tool for drought management and drought early warning.

1. Introduction

Drought is considered by many researchers to be the most complex but least understood of all natural hazards, affecting more people than any other hazard [1]. Drought is one of the major weather related disasters which is persisting over months or years. It can affect large areas and may have serious environmental, social and economic impacts. Globally, about 22% of the economic damage caused by natural disasters and 33% of the damage in terms of the number of persons affected can be attributed to drought [2]. These impacts depend on the severity, duration, and spatial extent of the precipitation deficit, as well as the socioeconomic and environmental vulnerability of affected regions [3]. Unlike the effects of a flood which can be immediately seen and felt, droughts build up rather slowly, creeping and steadily growing [4]. Droughts are typically classified into four types: meteorological, hydrological, agricultural and socioeconomic, and there are many drought indicators associated with each drought type [5,6]. Drought forecasting plays an important role in the mitigation of impacts of drought on water resources systems and water resources management [6–8].

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From a stochastic point of view, the problem of forecasting future values of a random variable can be seen as the determination of the probability density function of future values conditioned by past observations [9]. Yevjevich as reported in [10] was among the first at attempting a prediction of properties of droughts using the geometric probability distribution, defining a drought of k years as k consecutive years when there are no adequate water resources. Rao and Padmanabhan [11] investigated the stochastic nature of yearly and monthly Palmer's drought index (*PDI*) series to characterize them via valid stochastic models which may be used to forecast and to simulate the *PDI* series. Sen [12] derived exact probability distribution functions of critical droughts in stationary second order Markov chains for finite sample lengths on the basis of the enumeration technique and predicted the possible critical drought durations that may result from any hydrological phenomenon. Lohani and Loganathan [13] used *PDI* in a non-homogenous Markov chain model to characterize the stochastic behavior of drought and based on these drought characterizations an early warning system was used for drought management [14].

The main objective of this study is to build Hidden Markov Models (HMMs) for meteorological drought forecasting at short-medium term. The stochastic models presented in this study are based on SPI developed by McKee et al. [15] as drought index because there are a number of advantages arise from the use of the *SPI* index [14,16,17]. The primary advantage is that *SPI* is based on rainfall alone, so that drought assessment is possible even if other hydro-meteorological measurements are not available. The *SPI* is also not adversely affected by topography, it is defined over various timescales (3, 6, 9, ..., 72 months) and this allows to use it as short, medium and long-term drought index to describe drought conditions over a range of meteorological, hydrological and agricultural applications. In particular, analytical expressions of *SPI* forecasts are derived as the expectation of future *SPI* values conditioned on past monthly precipitation, under the hypothesis of normally distributed precipitation aggregated at different timescales k. Validation of the model was carried out with reference to precipitation series observed in 22 stations located in the Upper Blue Nile River Basin (UBNRB), Ethiopia. To the best of our knowledge, the issue on forecasting of meteorological drought using Hidden Markov Model so far has not been addressed. Some of the other studies about using of Markov chain models to predict the transition from a class of severity to another are listed in [18–20]. The approach presented herein provides not only a stochastic methodology to forecast the transition probability from a drought class to another but also the magnitude and duration of drought event. It is hoped that the proposed approach and our findings obtained in this study are useful for further research in the area of drought forecasting.

2. Methods and materials

2.1. Study region and data

The Blue Nile river, which starts its flow from Lake Tana and ends at the Ethiopian–Sudan border, is the largest tributary of the Nile river in terms of discharge and annually contributes 60–69% of runoff to the Nile river at Khartoum [21,22]. The Blue Nile river originates in the highlands of Ethiopia, and the Upper Blue Nile River Basin (UBNRB) is the part of the watershed of the Blue Nile river basin which is under the Ethiopian territory (Fig. 1). The altitude of the UBNRB ranges from 511 m to 4052 m and the Blue Nile and its tributaries have a general slope toward the northwest, however the slopes are steeper in the east than in the west and northeast areas of the UBNRB (Fig. 1).

Forty-eight years (January 1960 to December 2007) of daily precipitation data from 22 meteorological stations in the upper Blue Nile basin were used in this study to forecast drought events. The selected stations represent a good spatial coverage across the study region (Fig. 1). Daily precipitation records were first processed in terms of data gaps using neighboring stations to fill in missing precipitation values and then converted to monthly values and after that homogeneity test was applied to the data using several homogeneity tests included absolute and relative homogeneity tests. The precipitation over the Blue Nile basin varies from 1000 mm in the north-eastern part to 1450–2100 mm over the south-western part of the sub-basin [23].

The mean annual areal rainfall over the UBNRB, within the studied period, is 1260 mm as shown in Fig. 2. The rainfall distribution is highly variable both spatially – decreasing from the southwest to the east and northeast – and temporally, i.e. over the yearly seasons. Moreover, as the rainfall over the UBRNB is highly seasonal, the Blue Nile river also possesses a strongly-varying seasonal flood regime, whereby over 80% of the annual discharge occurs during the four months from July to October. The average annual flow of the Blue Nile at the Sudan–Ethiopian border is about 48,660 million m^3 which represents more than 40% of Ethiopia's total surface water resources [24]. Hence, the UBNRB represents a substantial water resource for Ethiopia and as well for the downstream countries Sudan and Egypt.

2.2. Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (*SPI*) is based on an equi-probability transformation of aggregated monthly precipitation into a standard normal variable and recommended by the World Meteorological Organization as a standard to characterize meteorological droughts [15,25,26]. The calculation of *SPI* requires that there are no missing data in the time series and the data record length is required to be at least 30 years [27,28]. McKee assumed an aggregated precipitation gamma distributed and used a maximum likelihood method to estimate the parameters of the distribution. In the most cases, the Gamma distribution is the distribution that best models observed precipitation data. Computation of the *SPI* involves the fitting of a gamma probability density function to a given frequency distribution of precipitation totals for a station [14,29]. The alpha and beta parameters of the gamma probability density function are estimated for each station, for each timescale of interest (1 month, 3 months, 12 months, 48 months, etc.) and for each month of the year.

After estimating coefficient alpha and beta the density of probability function is integrated with respect to, obtain an expression for cumulative probability that a certain amount of rain has been observed for a given month and for a specific timescale. The cumulative probability is then transformed into