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A gene–wavelet model for long lead time drought forecasting

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SUMMARY

Drought forecasting is an essential ingredient for drought risk and sustainable water resources management. Due to increasing water demand and looming climate change, precise drought forecasting models have recently been receiving much attention. Beginning with a brief discussion of different drought forecasting models, this study presents a new hybrid gene–wavelet model, namely wavelet–linear genetic programing (WLGP), for long lead-time drought forecasting. The idea of WLGP is to detect and optimize the number of significant spectral bands of predictors in order to forecast the original predictand (drought index) directly. Using the observed El Niño–Southern Oscillation indicator (NINO 3.4 index) and Palmer's modified drought index (PMDI) as predictors and future PMDI as predictand, we proposed the WLGP model to forecast drought conditions in the State of Texas with 3, 6, and 12-month lead times. We compared the efficiency of the model with those of a classic linear genetic programing model developed in this study, a neuro-wavelet (WANN), and a fuzzy-wavelet (WFL) drought forecasting models formerly presented in the relevant literature. Our results demonstrated that the classic linear genetic programing model is unable to learn the non-linearity of drought phenomenon in the lead times longer than 3 months; however, the WLGP can be effectively used to forecast drought conditions having 3, 6, and 12-month lead times. Genetic-based sensitivity analysis among the input spectral bands showed that NINO 3.4 index has strong potential effect in drought forecasting of the study area with 6–12-month lead times.

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1. Introduction

Drought forecasting is an essential ingredient in watershed management. In recent years, its importance is being intensified owing to increasing water demand and looming climate change (Mishra and Singh, 2010). The success of drought preparedness and mitigation depends upon timely information on the drought onset and propagation in time and space (Özger et al., 2012). This information may be obtained through precise drought forecasting models, which is normally generated using drought indices.

Many drought forecasting models have been developed in recent years (e.g., Rao and Padmanabhan, 1984; Sen, 1990; Bogradi et al., 1994; Lohani and Loganathan, 1997; Mishra and Desai, 2005; Cancelliere et al., 2007; Modarres, 2007; Fernandez et al., 2009; Özger et al., 2012). Mishra and Singh (2011) have provided a comprehensive review on different drought forecasting approaches.

In recent years, artificial intelligence (AI) techniques such as artificial neural network (ANN), fuzzy logic (FL), and genetic programing (GP) have been pronounced as a branch of computer science to model wide range of hydro-meteorological processes (Pesti et al., 1996; Whigham and Crapper, 2001; Dolling and Varas, 2002; Morid et al., 2007; Kisi and Guven, 2010; Özger et al., 2012; Nourani et al., 2013a). Successful application of fuzzy rule-based modeling for short term regional drought forecasting using two forcing inputs, El Niño–Southern Oscillation (ENSO) and large scale atmospheric circulation patterns (CP), was described by Pongracz et al. (1999). Mishra and Desai (2006) used both recursive and direct multi-step ANNs for up to 6-month LT drought forecasting and found that the recursive multi-step model is the best suited for 1 month LT. When a LT longer than 4 months was considered, the direct multi-step model outperformed the recursive multi-step models. Morid et al. (2007) developed an ANN-based drought forecasting approach with the LTs of 1–12 months using Effective Drought Index (EDI), SPI, and different combinations of past rainfalls. The results indicated that forecasts using EDI were superior to those using SPI for all LTs. Barros and Bowden (2008) applied self-organizing maps and multivariate linear regression analysis to forecast SPI at Murray-Darling Basin in Australia up to 12 months in advance.

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Owing to the limited ability of the above-mentioned AI techniques to forecast non-stationary phenomena, hybrid AI models were developed and suggested to forecast drought and successful results have also been reported (Kim and Valdes, 2003; Mishra and Singh, 2010; Belayneh and Adamowski, 2012; Özger et al., 2012; Belayneh et al., 2014). Mishra et al. (2007), using the SPI series, developed a hybrid ANN-ARIMA model for drought forecasting in Kansabati River Basin in India. The hybrid model was found to be more accurate than individual stochastic and ANN models up to a 6-month LT. Bacanli et al. (2009) developed an adaptive neuro fuzzy inference system (ANFIS) for drought forecasting using SPI in central Anatolia, Turkey. The authors pointed out that the hybrid method performs better than the classic ANN model. Özger et al. (2012) developed a hybrid wavelet–FL (WFL) model for long lead time drought forecasting using Palmer modified drought index (PMDI) series across the State of Texas and compared the WFL results with those of an ANN and a coupled wavelet–ANN (WANN) models. They found that the WFL had a significant improvement over the ad hoc FL, ANN, and hybrid WANN models. Belayneh et al. (2014), using SPI time series, developed hybrid WANN and wavelet-support vector regression (WSVR) models to forecast long-term drought in the Awash River Basin of Ethiopia. They compared the effectiveness of these models with those of ARIMA, ANN, and ad hoc support vector regression models and stated that the WANN model is the best one for 6 and 12-months LT drought forecasting in their study area.

Despite providing plausible forecasting accuracy, all the aforementioned ANN-based models provide implicit formulations with huge matrix of synaptic weights and biases. Thus, necessity for further studies in order to develop not only precise but also explicit models is still receiving serious attention. In recent years, different variants/advancements of genetic programing (GP) approach has been pronounced as a robust explicit method to solve wide range of modeling problems in water resources engineering such as rainfall-runoff modeling (Dorado et al., 2003; Nourani et al., 2012), evapotranspiration (Kisi and Guven, 2010), unit hydrograph determination (Rabuñal et al., 2007), sediment transport (Aytek and Kisi, 2008), sea level forecasting (Ghorbani et al., 2010), streamflow prediction (Danandeh Mehr et al., 2013a) and others. A comprehensive review on application of hybrid wavelet–AI models in hydrology has been provided by Nourani et al. (2014). The authors also highlighted and discussed the importance of available hybrid models for drought forecasting. Moreover, our review indicated that there is no research in the relevant literature examining the performance of any hybrid GP technique in drought forecasting. It is also important to understand different modeling methods as well as their benefits and limitations (Mishra and Singh, 2011). These are the main reasons inspired us to develop an explicit model based on one of the advancements of GP namely linear genetic programing (LGP) GP to forecast drought in this study.

It is already proven that the drought process contains high non-stationary and long-term patterns (seasonality) and classic AI techniques such as ANN and FL may not be sufficient for long LT drought forecasting (Özger et al., 2012). Therefore, our study was commenced with a data pre-processing, i.e. de-noising our predictor time series using continuous wavelet transform technique, and accomplished by a LGP–based model. In this study, based upon lagged values of drought index across the State of Texas along with NINO 3.4 index, symbolizing the sea surface temperature anomalies, we developed a hybrid wavelet–linear genetic programing (WLGP) model (here after gene–wavelet model) for long LT drought forecasting. For this aim, we initially applied wavelet transform to decompose the predictor time series into its major sub-series and then we employed a LGP technique to make forecasts. The LGP component of the model can handle the nonlinearity elements, while the wavelet component can deal with periodicity of the hydro-climatic variables. Furthermore, the performance of the proposed gene–wavelet model was compared with those of hybrid WANN and WFL models previously reported by Özger et al. (2012).

Since the black-box models are often case-sensitive, in the present study, we do not attempt to claim or assert superiority of a particular model over the others. The main goal of this paper is, for the first time, to introduce a new explicit gene–wavelet model (WLGP) for drought forecasting.

2. Wavelet transform

Wavelet transform (WT) provides multi-resolution of a signal in time and frequency domains and has been employed for studying non-stationary time series, where it is difficult to detect the time of occurrence of a particular event if Fourier transform (FT) is used (Özger et al., 2012). In other words, while FT separates a signal into sine-waves of various frequencies, WT separates a signal into shifted and scaled version of the original (or mother) wavelet (Özger, 2010). WT allows the use of long-time intervals for low frequency signals and shorter intervals for high frequency signals and is able to expose some statistical features of time series like trend and jump that other signal analysis techniques such as FT might miss (Danandeh Mehr et al., 2013a). Since the ENSO indicators (such as NINO 3.4 index) and drought occurrence have long time intervals to develop, low frequency components gain importance in comparison with high frequency. High frequency components of the NINO 3.4 index and PMDI series are detected with lower scales that refer to a compressed wavelet (Özger et al., 2012).

2.1. Continuous wavelet transform (CWT)

In mathematics, an integral transform (Tf) is particular kind of mathematical linear operator, which has the following form:

$$Tf(u) = \int_{t1}^{t2} K(t,u)f(t)dt \tag{1}$$

where $f(t)$ is an square-integrable function such as a continuous time series and K is a two variable, t and u, function called kernel (Danandeh Mehr et al., 2013b).

According to Eq. (1), any integral transform is specified by a choice of the kernel function. If function K is chosen as wavelet function, then CWT is (Mallat, 1998):

$$T(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} \Psi^{*}\left(\frac{t-b}{a}\right) f(t)dt \tag{2}$$

where $T(a, b)$ is the wavelet coefficients, $\Psi(t)$ is a mother wavelet function, in time and frequency domain, and $*$ denotes operation of complex conjugate.

The parameter a can be interpreted as a dilation ($a > 1$) or contraction ($a < 1$) coefficient of the $\Psi(t)$ corresponding to different scales of observation. The parameter b can be interpreted as a temporal translation (or shift) of the wavelet function, which allows the study of the signal $f(t)$ locally around the time b (Wu et al., 2009). The main property of wavelets is localized in both frequency (a) and time (b), whereas the Fourier transform is only localized in frequency (Danandeh Mehr et al., 2013b).

Appropriate selection of the type of mother wavelet to decompose input time series is one of the important tasks of modellers. It has been recommended that the suitable mother wavelet can be selected according to the shape pattern similarity between the mother wavelet and the investigated time series (Nourani et al., 2009b; Danandeh Mehr et al., 2013a; Onderka et al., 2013). A Brute-force search method has also been adopted as an alternative

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