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Hydrological Drought Class Transition Using SPI and SRI Time Series by Loglinear Regression

Jianzhu Li[1] · Shuhan Zhou[1] · Rong Hu[1]

Abstract Loglinear models for three-dimensional contingency tables was used with data from 21 rainfall stations and 7 hydrometric stations in the Luanhe river basin, northeast China, for short term prediction of drought severity class. Loglinear models were fitted to drought class transitions derived from standardized precipitation index (SPI) and standardized runoff index (SRI) time series to find which series was more suitable for hydrological drought class prediction 1 and 2 months ahead, respectively. Expected frequencies for two consecutive transitions between drought classes were first calculated, and based on this the predicted drought classes 1 and 2 months ahead were obtained. The results showed that despite the contingency tables of drought class transitions presented the maintenance of the precedent drought class, results of three-dimensional loglinear modeling presented good results when comparing predicted and observed drought classes. Only for a few cases predictions did not fully match the observed drought class, mainly for 2-month lead and when the SRI values are near the limit of the severity class predicted by SRI time series. Based on the correlation analysis of SPI and SRI, we presented the well-known method of hydrological drought class prediction by SPI time series. It was found that, using loglinear regression method, the accuracy of predictions for 2-month lead predicted by SPI time series was higher than those predicted by SRI time series. When we divided the SPI and SRI time series into 2 sub-periods (pre- and post-1980 where land cover changed), we got the same drought class prediction as that predicted by the entire SPI and SRI time series, which illustrated that changes in land use did not affect predictions of hydrological drought classes in the Luanhe river basin. It could be concluded that loglinear prediction of drought class transitions is a useful tool for short term hydrological drought warning, and the results could provide significant information for water resources managers and policy makers to mitigate drought effects.

Keywords Hydrological drought class prediction · Loglinear models · SPI and SRI

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1 Introduction

Drought is a multi-faceted phenomenon that occurs on different temporal and spatial scales and influenced a range of societal sectors that are dependent on climate and water resources (Wilhite 2000). Droughts rank first among all natural hazards when measured in terms of the number of people affected (Hewitt 1997; Wilhite 2000). The droughts are generally classified into four categories (Mishra and Singh 2010), which include meteorological drought, hydrological drought, agricultural drought and socio-economic drought. Meteorological drought is defined as a lack of precipitation over a region for a period of time. Hydrological drought is related to a period with inadequate surface and subsurface water resources which originated from meteorological drought. Agriculture drought refers to a period with declining soil moisture and consequent crop failure without any reference to surface water resources. And socio-economic drought is associated with failure of water resources systems to meet demands for an economic good.

For drought monitoring and warning, several indices, depending on hydro-meteorological parameters or relying on probabilities of drought occurrence, were presented. Among the drought indices currently produced, some indices are perceived to be more broadly useful and easy to implement (Tsakiris et al. 2007; Mendicino et al. 2008; Tabari et al. 2013). The standardized precipitation index (SPI) was first presented by Mckee et al. (1993) based on the long-term precipitation record for a given period. This long-term record is fitted to a probability distribution, which is then transformed to a normal distribution so that the mean SPI for the location and desired period is zero. The advantage of SPI is that it can be calculated for a range of time scales. SPI has been used for studying different aspects of droughts, for example, forecasting (Mishra and Desai 2005a; Mishra et al. 2007), frequency analysis (Mishra et al. 2009; Huang et al. 2014), spatio-temporal analysis (Mishra and Desai 2005b) and climate impact studies (Mishra and Singh 2011). Palmer drought index (PDI) was the first comprehensive effort to assess the total moisture status of a region. The index has been used to illustrate the areal extent and severity of various drought episodes (Palmer 1967) and to investigate the spatial and temporal drought characteristics (Soule 1993) as well as to explore the periodic behavior of droughts (Rao and Padmanabhan 1984), and drought forecasting (Kim and Valdes 2003; Özger et al. 2009). Standardized runoff index (SRI) is based on the concept of standardized precipitation index (SPI). Shukla and Wood (2008) derived standardized runoff index (SRI) which incorporates hydrologic processes that determine the seasonal loss in streamflow due to the influence of climate. As a result, on month to seasonal time scales SRI is a useful complement to SPI for depicting hydrological aspects of droughts. Besides, many other drought indices have been developed for different drought categories (Byun and Wilhite 1999; Narasimhan and Srinivasan 2005; Vasiliades et al. 2011).

Drought forecasting is a critical component of drought hydrology which plays a major role in risk management, drought preparedness and mitigation (Mishra and Singh 2011). There has been considerable work done on modeling various aspects of drought, such as identification and prediction of its duration and severity. Several methods have been developed and applied in drought forecast, such as regression models (Liu and Negron-Juarez 2001), time series analysis (Han et al. 2010), probability models (Haan 2002; Cancelliere et al. 2007), Artificial neural network model (Mishra and Desai 2006) and long-lead drought forecasting using climate indices as well as the periodic nature of hydro-meteorological variables (Morid et al. 2006; Schubert et al. 2009). However, forecasting of when a drought is likely to begin or to come to an end is extremely difficult. An adequate lead-time, i.e., the period between the release of the prediction and the actual onset of the predicted drought hazard, is often more

important than the accuracy of the prediction for drought preparedness. The accurate predicted lead-time makes it possible for decision and policy makers to timely implement policies and measures to mitigate the effects of drought (Nichols et al. 2005).

Developing prediction and early warning tools appropriate to the climatic and agricultural conditions prevailing in different drought prone areas is a current research challenge. The stochastic properties of the SPI time series were explored for predicting drought class transitions using Markov chains modeling (Paulo et al. 2005; Paulo and Pereira 2007; Paulo and Pereira 2008) and loglinear models were also first used with this purpose (Paulo et al. 2005). Loglinear models were successfully applied to analyze meteorological drought class transitions and to search for impacts of climate change on drought frequency and severity (Moreira et al. 2006; Moreira et al. 2008). Similarly, the models may be used to predict hydrological drought class by SRI time series.

Drought prediction is of vital significance for drought preparedness and mitigation. Rossi et al. (2007) introduced drought management decision support system, which was able to forecast the occurrence of a drought and to realize a water resources management focused on the mitigation of the economic and social effects of water shortage. This system has been currently used in the Júcar river basin. Using a forecast precipitation index (FPI) in 2001 in the United States, water managers decided whether to pay farmers to suspend irrigation (Steinemann 2006). Changnon et al. (2003) reviewed the impacts of spring and summer droughts forecasts in March 2000 for five Midwestern states, and they pointed out this forecast failure led to a loss of credibility over future use of climate forecasts by water managers. Therefore, accurate short time drought prediction is useful for alerting water managers and decision or policy makers about the need to enforce appropriate preparedness measures before a drought is effectively installed, or to prepare for a post-drought period.

In this study, Luanhe river basin was selected as the study area, for its great significance to supply water to Tianjin, an important metropolis of China. Water resources deficiency was focused on for the past decades. The aim of this research is to predict hydrological drought class by loglinear regression with the SRI and SPI time series in seven sub-watersheds of Luanhe river basin, respectively, and find which series is more suitable for drought class forecast for 1 and 2 months ahead, respectively. The novelty of this paper is to predict hydrological drought class with SPI time series, but not only SRI time series, by loglinear regression method to improve the model's accuracy.

2 Study Area

The Luanhe river basin is selected in this study for its significance to Tianjin city, a very large city in China, for water supply. The government made a plan in 1983 to introduce water of a billion cubic meters to Tianjin per year from Luanhe river basin in order to mitigate water shortage in Tianjin. However, the actual amount of water transferred to Tianjin was less than the planned in several years, especially in the last decade due to meteorological and hydrological droughts in the basin. The basin had been disturbed severely by soil and water conservation after 1980, and the average annual runoff had decreased by 30 % after 1980 due to rainfall reduction and soil and water conservation (Li and Feng 2007).

The Luanhe river basin, located in the northeast part of China, has a drainage area of 33,700 km^2, and lies between 115°40′~119°20′E longitude and 39°10′~42°35′N latitude with the elevation ranging from 2 to 2205 m (the mean elevation is 766 m). About 98 % of the drainage

area is mountainous region and about 2 % is plain. Panjiakou reservoir watershed consists of six sub-watersheds, i.e., Luanhe (controlled by Sandaohezi hydrometric station), Baohe, Laoniuhe, Wuliehe, Yixunhe and Liuhe sub-watersheds (Fig. 1). While Xiaoluanhe, Yimatuhe and Xingzhouhe are the sub-catchments of Luanhe sub-watershed (controlled by Sandaohezi hydrometric station). The watershed receives an average precipitation of 560 mm, mostly in the summer (70–80 %), especially in July and August, and an average runoff of 4.69 billion cubic meters per year. The flood is often resulted from rainstorm, and also in July and August. Because of the short duration and high intensity of the rainstorms, the flood is of high peak and large amount and the duration of the flood is between 3 and 6 days. The average temperature is between −0.3~11 °C, and gradually lower from southeast to northwest. The average potential evapotranspiration reaches 950~1150 mm per year, and the highest can reach 1801 mm per year. The average absolute humidity is 9.6 mbar, and the average relative humidity is 60–70 %.

The drought events in the Luanhe river basin mainly occurred in 1961, 1963, 1968, 1972, 1980~1984, 1997~2005, 2007 and 2009, and we can see consecutive drought events lasted for several years during the last decade (Haihe River Water Conservancy Commission 2009). The consecutive drought in the 21st century in the Luanhe river basin resulted in deficient water
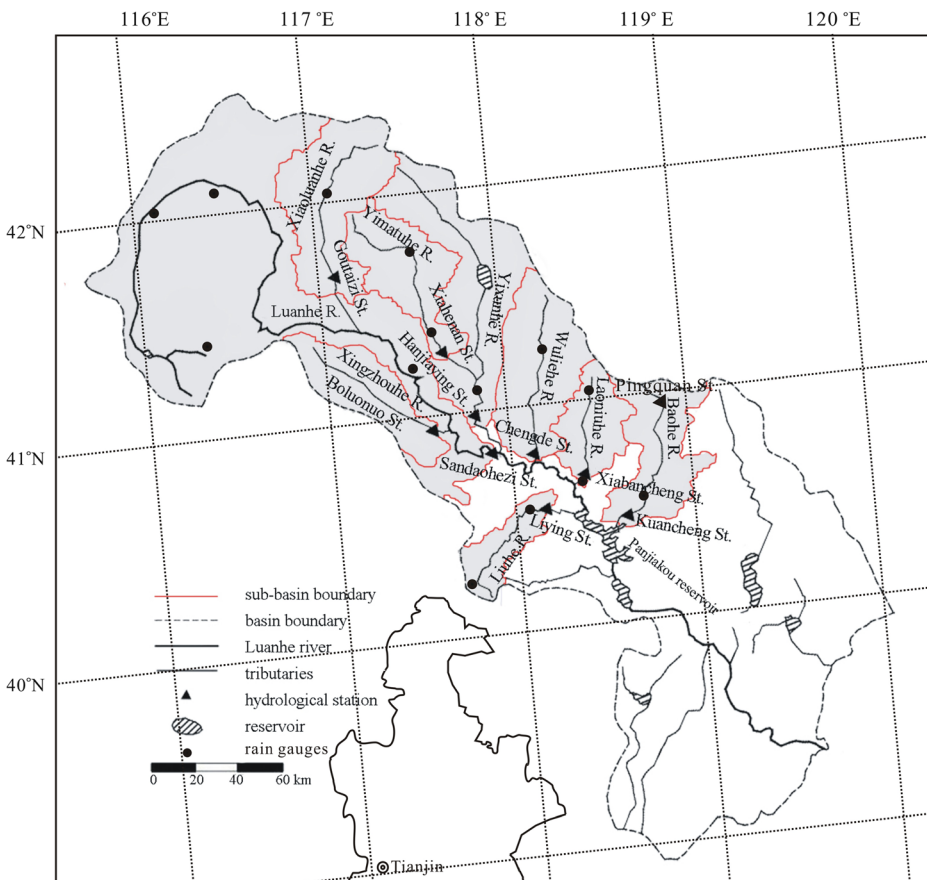
Fig. 1 The Luanhe river basin and its tributaries

Table 1 Long-term monthly average precipitation (P with unit of mm) and runoff (R with unit of 10^6 m^3) of the sub-watersheds

Watershed		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Luanhe	P	1.7	4.1	9.6	20.6	42.6	86.3	147.5	113.7	52.2	23.5	6.4	2.1
	R	8.6	9.7	25.9	57.5	27.3	38.2	86.1	121.9	68.9	49.7	31.1	12.5
Yixunhe	P	1.6	4.1	9.6	20.2	42.0	81.7	142.7	110.7	53.9	22.3	6.7	1.9
	R	4.5	5.0	14.9	16.6	10.3	24.5	76.4	86.5	42.3	24.0	15.5	7.2
Wuliehe	P	1.8	4.1	8.1	20.8	44.6	86.5	144.8	116.9	48.9	22.8	6.4	2.0
	R	3.2	3.4	4.8	4.3	2.5	10.7	49.5	59.0	24.3	14.7	9.1	5.3
Liuhe	P	1.9	4.4	9.7	24.8	46.5	95.0	207.6	150.0	57.3	26.3	7.0	2.5
	R	2.5	2.3	2.4	2.2	1.9	3.8	30.2	40.2	14.6	7.6	4.9	3.4
Baohe	P	2.1	3.6	8.7	24.2	44.2	88.1	146.6	122.1	48.1	25.7	8.0	2.7
	R	0.9	0.9	0.9	0.8	0.5	1.6	5.6	7.1	3.0	1.7	1.3	1.0
Laoniuhe	P	1.8	2.7	7.7	23.3	42.9	86.6	161.1	131.4	49.9	24.3	6.2	2.2
	R	3.5	3.5	3.7	3.0	2.1	5.5	18.5	28.5	14.1	8.9	6.3	4.4
Xingzhouhe	P	2.1	4.6	9.5	20.8	42.0	79.3	148.1	115.5	56.2	25.4	7.0	2.8
	R	1.8	2.0	2.7	2.4	1.8	3.9	13.0	22.1	11.3	6.0	4.2	2.6

supply to Tianjin city, and water transfer from the Yellow river to Tianjin was carried out several times. The long-lasting drought aggravated agricultural production and water crisis in Tianjin city.

The land use types in the study area are forest, grassland, agricultural land, water and unutilized land. Land use changed a little during 1956–2012. But soil and water conservation in the area was carried out after 1980, and stored part of the generated runoff, so less runoff flow to the outlet of the basins.

In this study, Liuhe, Baohe, Wuliehe, Yixunhe, Laoniuhe, Xingzhouhe, and Luanhe (controlled by Sandaohezi station) sub-watersheds were selected as the study area (Fig. 1). The sub-watersheds range in area from 626 to 17,100 km^2, and each with a hydrometric station at the outlet. The long-term monthly average precipitation and runoff of the sub-watersheds are listed in Table 1.

3 Data and Methods

3.1 Data

Monthly rainfall data of 21 rain gauges covering the period from 1956 to 2011 were used to calculate SPI for 12-month time scale. And monthly runoff data of seven hydrometric stations covering the period from 1956 to 2011 were used to calculate SRI for 12-month time scale. All the data were provided by Hydrology and Water Resource Survey Bureau of Hebei Province. The location of the selected hydrometric stations is shown in Fig. 1.

3.2 Methods

3.2.1 SPI and SRI

SPI is an indicator of meteorological droughts, which is mainly caused by a deficiency of precipitation. SPI has a very straightforward classification of different drought severities.

When SPI is below −1.5, the drought condition is considered severe; when it reaches below −2.0 it is considered extreme severe (Table 1). SPI is a probability based index, so the heaviness or lowness of a precipitation event in the SPI is relative to the rainfall characteristics of that area. Data from the long-term record are first fitted by a Gamma probability distribution, and the calculation steps had been given in many other papers (McKee et al. 1993; Liu et al. 2012). SRI is an indicator of hydrological droughts, which was developed by SPI concept. The calculation of SRI was followed by the same procedure as SPI (Shukla and Wood 2008).

In the Luanhe river basin, Ma et al. (2013) used the classification limit values in Table 2 and compared SPI with other three drought indices (precipitation anomaly index and runoff anomaly index, precipitation Z index) to reflect the historical drought events. Precipitation anomaly index is calculated by subtracting the long-term average precipitation from monthly precipitation and dividing the difference by long-term average precipitation. Runoff anomaly index is proposed based on the concepts of precipitation anomaly index. Precipitation Z index assumes that precipitation data follow the Pearson Type III distribution and is related to Wilson-Hilferty cube-root transformation from chi-square variable to the Z-scale. The value is calculated as:

$$CZI = \frac{6}{C_{st}} \left(\frac{C_{st}}{2} ZScore_t + 1 \right)^{1/3} - \frac{6}{C_{st}} + \frac{C_{st}}{6} \tag{1}$$

where, CZI is precipitation Z index. C_{st} is coefficient of skewness for t time step. Zscore is the statistical Zscore and will be computed for the same time step t. It was pointed out that SPI could capture the recorded droughts better than precipitation Z index, precipitation anomaly index and runoff anomaly index. Feng et al. (2014) showed the good performance of 12-month time scale SPI for drought characterization in the Luanhe river basin and meteorological drought class transition. So, in this study, 12-month time scale SPI and SRI were selected to analyze the hydrological drought class transition in the study area. In Mishra and Cherkauer's previous work (2009), drought severity for the SRI was identified using the same ranges defined for the SPI, therefore, we adopted this point in this study. The severity drought classes adopted are defined in Table 2. They are proposed by Moreira et al. (2008) by grouping the severe and extremely severe drought classes for modeling purpose since transitions referring to the extremely severe droughts are much less frequent than other classes; thus, a possible bias is avoided.

3.2.2 Loglinear Models with Three-Dimensions

Loglinear modeling (Agresti 1990), which describe association patterns among categorical variables, is performed for the cell counts contingency tables. The Poisson sampling model for counts is usually used for counts in contingency tables and assumes that they are independent

Table 2 Drought class classification of SPI and SRI (from Moreira et al. 2008)

Code	Drought classes	SPI or SRI values
1	Non-drought	SPI≥0
2	Near normal	−1<SPI<0
3	Moderate	−1.5<SPI≤−1
4	Severe/extreme	SPI≤−1.5

Poisson random variables. Three-dimensional loglinear models aim a fitting the observed frequencies of transitions between each drought class, denoted as O_{ijk}, and to model the corresponding expected frequencies, denoted as E_{ijk}, which are the estimates of the observed frequencies for each cell of a three-dimensional contingency table (Table 3). In the three-dimensional contingency table, both drought classes at month t-2 and t-1 can be hydrological drought classes, or meteorological drought classes, but that at month t is hydrological drought class. In the former condition, the hydrological drought class at month t will be predicted by SRI time series, and the latter indicates the hydrological drought prediction by SPI time series.

The observed frequencies (O_{ijk}) are the response variable for the loglinear models and refer to the observed number of transitions between the drought class i at month t-2 and drought class j at month t-1 and drought class k at month t. The observation O_{111} is the number of times that a given site stays for three consecutive months in drought class 1. So, the three-dimensional loglinear models allow modeling the expected frequencies of drought class transitions corresponding to a 2-month step transition from class i to class j and from class j to class k. The procedures of drought class prediction using loglinear regression are as follows:

(1) The observed frequencies were first calculated according to the meteorological or hydrological drought class time series.
(2) Loglinear regression model was established and the model parameters were estimated by maximum likelihood method.
(3) Then the odds and confidence intervals were calculated. An odds is a ratio of expected frequencies, and represents the number of times that it is more, less, or equally probable the occurrence of a certain event instead of another (Moreira et al. 2008). When the confidence intervals for a given odds include the value 1 it means that the drought transition from class i to class j to class k and the drought transition from class i to class j to class l, are not significantly different.
(4) Drought class transition was predicted.

The details of loglinear models could be referred to Moreira et al. (2008).

Rate of accuracy is used to evaluate the performance of loglinear regression model in predicting drought class with SPI and SRI time series, respectively, which is defined as the total numbers of month divided by the numbers of month for which the predicted and observed hydrological drought classes match. It can be expressed as Eq. (2).

$$R_a = \frac{M}{N_{total}} \qquad (2)$$

where R_a is the rate of accuracy, M is the numbers of month that the predicted drought class matches the observed, N_{total} is the total numbers of month.

4 Results

4.1 Hydrological Drought Class Transition Predicted by SRI

Table 4 presents for several hydrometric stations the values of the expected number of transitions between hydrological drought classes for two consecutive months. As it can be seen, the highest values occur for the transitions that imply the maintenance of the precedent hydrological drought

Table 3 Three-dimensional contingency table for two consecutive transitions between drought classes

Drought class at month t-2	Drought class month t															
	1				2				3				4			
	Drought class month t-1				Drought class month t-1				Drought class month t-1				Drought class month t-1			
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1	O_{111}	O_{121}	O_{131}	O_{141}	O_{112}	O_{122}	O_{132}	O_{142}	O_{113}	O_{123}	O_{133}	O_{143}	O_{114}	O_{124}	O_{134}	O_{144}
2	O_{211}	O_{221}	O_{231}	O_{241}	O_{212}	O_{222}	O_{232}	O_{242}	O_{213}	O_{223}	O_{233}	O_{243}	O_{214}	O_{224}	O_{234}	O_{244}
3	O_{311}	O_{321}	O_{331}	O_{341}	O_{312}	O_{322}	O_{332}	O_{342}	O_{313}	O_{323}	O_{333}	O_{343}	O_{314}	O_{324}	O_{334}	O_{344}
4	O_{411}	O_{421}	O_{431}	O_{441}	O_{412}	O_{422}	O_{432}	O_{442}	O_{413}	O_{423}	O_{433}	O_{443}	O_{414}	O_{424}	O_{434}	O_{444}

Table 4 Expected frequencies for two consecutive transitions between drought classes

Drought class month t-2	Drought class at month t															
	1				2				3				4			
	Drought class month t-1				Drought class month t-1				Drought class month t-1				Drought class month t-1			
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
Sandaohezi																
1	**282.7**	2.3	0.0	0.1	11.1	10.7	0.2	0.0	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.1
2	10.1	8.9	0.1	0.0	1.9	**190.9**	5.4	0.0	0.1	13.1	2.0	0.0	0.1	0.2	1.6	0.2
3	0.2	0.9	0.1	0.0	0.0	12.3	2.8	0.0	0.0	34.8	**42.8**	0.5	0.0	0.0	2.3	3.7
4	0.1	0.0	0.0	0.1	0.1	0.1	0.7	0.2	0.0	0.1	3.2	3.7	0.0	0.0	0.2	**36.0**
Boluonuo																
1	**297.5**	2.5	0.1	0.1	12.2	11.6	0.2	0.0	0.1	0.2	0.0	0.0	0.2	0.0	0.0	0.1
2	11.4	10.4	0.2	0.0	1.8	**183.9**	3.6	0.0	0.1	9.7	2.3	0.1	0.0	0.0	0.1	0.2
3	0.1	0.2	0.0	0.0	0.0	9.2	0.9	0.0	0.1	38.3	**45.2**	0.6	0.1	0.3	2.9	2.8
4	0.2	0.0	0.0	0.1	0.2	0.3	1.4	0.3	0.0	0.0	1.5	2.6	0.0	0.0	0.3	**35.0**
Hanjiaying																
1	**251.9**	1.2	0.0	0.0	13.9	13.9	0.2	0.0	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.1
2	13.0	11.4	0.6	0.0	1.1	**198.9**	8.2	0.0	0.1	15.5	3.5	0.0	0.1	0.2	2.6	0.2
3	1.0	1.5	0.5	0.0	0.0	12.3	2.8	0.0	0.1	30.2	**37.4**	0.5	0.0	0.0	3.3	5.7
4	0.1	0.0	0.0	0.1	0.1	0.9	1.9	1.1	0.0	0.3	3.1	4.7	0.0	0.0	0.2	**34.1**
Chengde																
1	**288.8**	1.3	0.0	0.0	10.0	9.8	0.1	0.0	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.0
2	10.1	8.8	0.1	0.0	1.0	**192.7**	3.5	0.0	0.0	10.6	3.4	0.0	0.0	0.0	0.1	0.0
3	0.1	0.9	0.0	0.0	0.0	7.5	0.5	0.0	0.0	39.2	**47.0**	0.8	0.0	0.1	4.5	4.3
4	0.1	0.0	0.0	0.1	0.1	2.0	0.9	2.0	0.0	0.2	1.7	2.2	0.0	0.0	0.5	**34.7**
Liying																
1	**287.3**	1.0	0.1	0.0	14.3	12.9	0.7	0.1	1.2	1.4	0.5	0.1	0.2	0.0	0.0	0.2
2	14.3	11.4	0.3	0.0	0.8	**172.9**	4.5	0.0	0.0	9.4	1.7	0.0	0.1	0.2	1.6	0.3
3	1.2	2.4	0.5	0.0	0.0	7.8	1.4	0.0	0.1	37.8	**45.8**	0.6	0.0	0.1	4.3	5.7
4	0.3	0.3	0.3	0.3	0.0	0.5	0.6	1.1	0.0	0.5	4.0	4.6	0.0	0.0	0.3	**32.0**
Pingquan																
1	**299.8**	0.5	0.0	0.1	11.8	11.9	0.2	0.1	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.1
2	12.1	11.6	0.2	0.1	0.3	**182.4**	2.7	0.0	0.0	9.9	4.1	0.1	0.0	0.0	0.2	0.0
3	0.1	0.1	0.0	0.0	0.0	7.8	0.3	0.0	0.1	33.0	**39.3**	2.7	0.0	0.2	7.4	6.4
4	0.1	0.0	0.0	0.1	0.1	2.0	1.9	2.0	0.0	0.1	3.6	4.3	0.0	0.0	1.5	**22.6**
Xiabancheng																
1	**296.7**	2.3	0.1	0.1	11.2	10.7	0.1	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.1
2	9.4	8.0	0.7	0.0	1.7	**176.3**	4.1	0.0	0.0	10.7	2.3	0.0	0.0	0.0	0.1	0.1
3	0.9	0.8	0.4	0.0	0.1	8.9	1.1	0.0	0.1	45.2	**52.5**	0.4	0.1	0.2	4.9	4.9
4	0.1	0.0	0.0	0.1	0.1	0.1	0.8	0.1	0.0	0.1	4.2	4.7	0.0	0.0	0.2	**31.0**

classes (numbers in bold). A strong diagonal tendency is shown in the contingency tables indicating the self-perpetuating characteristic trend of hydrological droughts.

The lowest values in Table 4 refer to the direct transitions from a given drought class to another two or three categories more or less severe than the first one, e.g., from the severe drought to non-drought. These transitions have a very low probability because droughts do not initiate or disappear suddenly, while develop gradually. Table 5 presents the validation of the loglinear modeling by comparing the actual SRI drought class categories calculated from observed discharge data with the predictions 1 and 2 month ahead in Sandaohezi station for 2000 to 2003 consecutive droughts. The observed drought classes at month t-2 and t-1, and the observed and predicted drought classes for month t and $t+1$, i.e., with 1 and 2 month lead are presented. When the probability that a site will be in a given drought class is not significantly different from the probability that it would be in a next severity class, then the prediction refers to both drought classes, e.g., "2 or 3" meaning that the probabilities for transitions into the classes 2 to 3 are similar. The numbers with "*" refer to cases where the predicted hydrological drought classes are not in agreement with the observed. It is found hydrological drought class

Table 5 Comparison between observed and SRI-based predicted hydrological drought classes during 2000~2003 for Sandaohezi station (January, 2000 to December, 2003)

Date (month t)	Drought class at month		Drought class at month t		Drought class at month $t+1$		Drought class at month		Drought class at month t		Drought class at month $t+1$	
	t-2	t-1	Obs.	Pred.	Obs.	Pred.	t-2	t-1	Obs.	Pred.	Obs.	Pred.
	2000						2001					
Jan	4	4	4	4	4	4	3	3	3	2 or 3	3	2 or 3
Feb	4	4	4	4	4	4	3	3	3	2 or 3	2	2 or 3
Mar	4	4	4	4	4	4	3	3	2	2 or 3	2	2 or 3
Apr	4	4	4	4	4	4	3	2	2	2 or 3	2	2
May	4	4	4	4	4	4	2	2	2	2	2	2
Jun	4	4	4	4	4	4	2	2	2	2	2	2
Jul	4	4	4	4	3*	4*	2	2	2	2	3*	2*
Aug	4	4	3*	4*	3*	4*	2	2	3*	2*	4*	2*
Sep	4	3	3	3	3	2 or 3	2	3	4*	3*	4*	2 or 3*
Oct	3	3	3	2 or 3	3	2 or 3	3	4	4	4	4	4
Nov	3	3	3	2 or 3	3	2 or 3	4	4	4	4	4	4
Dec	3	3	3	2 or 3	3	2 or 3	4	4	4	4	4	4
	2002						2003					
Jan	4	4	4	4	4	4	4	3	3	3	3	2 or 3
Feb	4	4	4	4	4	4	3	3	3	2 or 3	3	2 or 3
Mar	4	4	4	4	4	4	3	3	3	2 or 3	3	2 or 3
Apr	4	4	4	4	4	4	3	3	3	2 or 3	3	2 or 3
May	4	4	4	4	4	4	3	3	3	2 or 3	3	2 or 3
Jun	4	4	4	4	4	4	3	3	3	2 or 3	3	2 or 3
Jul	4	4	4	4	4	4	3	3	3	2 or 3	3	2 or 3
Aug	4	4	4	4	4	4	3	3	3	2 or 3	3	2 or 3
Sep	4	4	4	4	4	4	3	3	3	2 or 3	2	2 or 3
Oct	4	4	4	4	4	4	3	3	2	2 or 3	2	2 or 3
Nov	4	4	4	4	3*	4*	3	2	2	2 or 3	3*	2*
Dec	4	4	3*	4*	3*	4*	2	2	3*	2*	3*	2*

Table 6 The rate of accuracy of hydrological droughts prediction by SRI and SPI time series, respectively

Stations	Predicted by SRI time series		Predicted by SPI time series	
	1 month lead (%)	2 month lead (%)	1 month lead (%)	2 month lead (%)
Sandaohezi	93.7	86.6	91.2	91.0
Boluonuo	93.5	87.5	91.8	89.0
Hanjiaying	90.9	76.0	90.7	89.0
Chengde	92.4	86.1	86.8	86.4
Liying	90.9	80.1	89.8	87.3
Pingquan	92.3	85.0	85.8	85.4
Xiabancheng	93.5	87.9	90.1	89.6

predictions at month $t+1$ are not as accurate as those at month t at Sandaohezi station, as well as other stations (not listed).

Table 6 lists the rate of accuracy of the prediction from 1956 to 2011 in all hydrometric stations. It can be observed that the rates of prediction accuracy with 1 month lead are relatively high with more than 90 %, and the rates with 2 month lead are relatively low with 80~90 % at most stations, specifically at Hanjiaying station with a lower value of 76.0 %. Thus we try to look for another perspective to predict hydrological drought classes by SPI time series in the next section.

4.2 Hydrological Drought Class Transition Predicted by SPI

4.2.1 Correlation Analysis of SPI and SRI

Since runoff is caused by precipitation in the Luanhe river basin, and SRI is presented based on SPI concept, there must be some relationship between SPI and SRI. Nalbantis and Tsakiris (2009) regressed streamflow drought index (SDI) on concurrent SPI based on a common period of data with and without delay, and the regression coefficient was significantly high. They predicted SDI values by the regression equations, and found a meteorological drought of certain severity produced a hydrological drought of lower severity. In this study, correlation

Table 7 Correlation coefficients (R^2) between SPI and SRI for different lag times

Sub-watersheds	Lag time				
	0 month	1 month	2 month	3 month	4 month
Liuhe	0.762	**0.802**	0.770	0.730	0.669
Baohe	0.458	0.512	0.545	0.565	**0.570**
Laoniuhe	0.562	0.604	**0.613**	0.600	0.568
Xingzhouhe	0.495	0.555	**0.558**	0.540	0.504
Wuliehe	0.508	**0.544**	0.526	0.502	0.461
Luanhe (Sandaohezi station)	0.541	**0.576**	0.566	0.543	0.510
Yixunhe	0.638	**0.644**	0.600	0.550	0.486

Note: The values in bold indicate the highest correlation coefficient, and were assumed to be the reasonable lag time

analysis between SPI and SRI was done in the selected sub-watersheds. There may be a period of lag time for SRI from SPI, indicating that hydrological drought can not be recognized until several months after meteorological droughts. The correlation coefficients for different lag times were shown in Table 7. There is 1 or 2 months lag time for hydrological droughts from meteorological droughts in almost all the sub-watersheds. Therefore, it may be inferred that hydrological drought class predictions 1 or 2 month lead using meteorological drought class could be feasible.

Tsakiris et al. (2013) have stated that streamflow is a composite variable since it includes ingredients of surface runoff, subsurface runoff and baseflow. They also found the groundwater recharge deficit occurred some months after the initial precipitation deficit. Therefore, 1 or 2 months lag time for hydrological droughts from meteorological droughts seems reasonable.

4.2.2 Hydrological Drought Class Prediction by Meteorological Drought Class

Table 8 presents the validation of the loglinear modeling by comparing the actual SRI drought class categories calculated from observed discharge data with the predictions 1 and 2 month ahead using SPI drought class in Sandaohezi station for 2000~2003 consecutive droughts. The numbers with "*" refer to cases where the predicted hydrological drought classes are not in agreement with the observed. It is found the numbers of month with probabilities for transitions into the neighboring classes are higher than those predicted by SRI time series, which was the case in other stations as well. However, hydrological drought class predicted by SPI time series agrees well with the observed to a large extent.

Table 6 also lists the rates of accuracy of the hydrological drought class prediction by SPI time series from 1956 to 2011 in all hydrometric stations. It can be observed that, similar with the results predicted by SRI, the rates of prediction accuracy with 1 month lead are relatively high with more than 90 %, and the rates with 2 month lead are relatively low with 80~90 % at most stations. However, 2-month lead predictions by SPI have a higher accuracy than those predicted by SRI, because of the lag time of hydrological drought from meteorological drought. The accuracy rate in Hanjiaying station increased from 76.0 to 89.0 %.

4.3 Do Changes in Land Use Affect Predictions of Hydrological Drought Class

Land use and land cover changed after 1980, i.e., several small reservoirs and large numbers of check dams (about 80 thousand) were built since that time, which resulted in runoff decrease by about 30 % (Li and Feng 2007). Li et al. (2014) analyzed the annual rainfall trend of the same sub-watersheds in this paper, and they found a decreasing trend during 1956–2010. Wang et al. (2013) proved that human activities should be mainly responsible for the reduction of the streamflow in the Luanhe River basin by hydrological model method, hydrological sensitivity method and climate elasticity method. They relied on the historical data during 1957–2000, and found that the relationship between precipitation and streamflow had changed abruptly in 1979. Sixty-one, 67 and 57 % of streamflow reduction in the Luanhe River basin were attributed to human activities by these three methods, respectively. All the previous studies in Luanhe river basin illustrated that runoff decrease was caused by both natural anthropogenic influence. The decrease in runoff led to increased hydrological drought severity downstream, which may affect the predictions of hydrological drought classes.

Table 8 Comparison between observed and SPI-based predicted hydrological drought classes during 2000~2003 for Sandaohezi station (January, 2000 to December, 2003)

Date (month t)	Meteorological drought class at month		Hydrological drought class at month t		Hydrological drought class at month t+1		Meteorological drought class at month		Hydrological drought class at month t		Hydrological drought class at month t+1	
	t-2	t-1	Obs.	Pred.	Obs.	Pred.	t-2	t-1	Obs.	Pred.	Obs.	Pred.
	2000						2001					
Jan	4	4	4	3 or 4	4	3 or 4	1	1	3*	1 or 2*	3	2 or 3
Feb	4	4	4	3 or 4	4	3 or 4	1	1	3*	1 or 2*	2	2 or 3
Mar	4	4	4	3 or 4	4	3 or 4	1	1	2	1 or 2	2	1 or 2
Apr	4	4	4	3 or 4	4	3 or 4	1	1	2	1 or 2	2	1 or 2
May	4	4	4	3 or 4	4	3 or 4	1	1	2	1 or 2	2	1 or 2
Jun	4	4	4	3 or 4	4	3 or 4	1	1	2	1 or 2	2	1 or 2
Jul	4	4	4	3 or 4	3	3 or 4	1	1	2	1 or 2	3*	1 or 2*
Aug	4	2	3	3	3	3	1	2	3*	1 or 2*	4*	2 or 3*
Sep	2	1	3	2 or 3	3	2 or 3	2	3	4*	2*	4	3 or 4
Oct	1	1	3	2 or 3	3	2 or 3	3	4	4	3 or 4	4	3 or 4
Nov	1	2	3*	1 or 2*	3	2 or 3	4	4	4	3 or 4	4	3 or 4
Dec	2	1	3*	1 or 2*	3	2 or 3	4	4	4	3 or 4	4	3 or 4
	2002						2003					
Jan	4	4	4	3 or 4	4	3 or 4	2	2	3*	1 or 2*	3	1 or 2
Feb	4	4	4	3 or 4	4	3 or 4	2	2	3*	1 or 2*	3	2 or 3
Mar	4	4	4	3 or 4	4	3 or 4	2	2	3*	1 or 2*	3*	2 or 3*
Apr	4	4	4	3 or 4	4	3 or 4	2	2	3	2 or 3	3*	2 or 3*
May	4	4	4	3 or 4	4	3 or 4	2	2	3	2 or 3	3	2 or 3
Jun	4	4	4	3 or 4	4	3 or 4	2	2	3	2 or 3	3	2 or 3
Jul	4	4	4	3 or 4	4	3 or 4	2	3	3	2	3	2 or 3
Aug	4	4	4	3 or 4	4	3 or 4	3	2	3	2 or 3	3	2 or 3
Sep	4	3	4	4	4	3 or 4	2	2	3*	1 or 2*	2	1 or 2
Oct	3	3	4	3 or 4	4	3 or 4	2	1	2	1 or 2	2	1 or 2
Nov	3	2	4	3 or 4	3*	1 or 2*	1	1	2	1 or 2	3*	1 or 2*
Dec	2	2	3*	1 or 2*	3*	1 or 2*	1	2	3*	1 or 2*	3*	1 or 2*

To check our assumption, the SPI and SRI time series are divided into two parts as pre and post 1980 based on the change point derived by Feng et al. (2008), and the predictions of hydrological drought classes are carried out by the time series before and after 1980, respectively. However, the predicted results are completely the same with those using the entire SPI and SRI time series (Tables 5 and 8). It was concluded that changes in land use did not affect predictions of hydrological drought class in the Luanhe river basin.

5 Discussion and Conclusions

The prediction of hydrological drought class 1 and 2 month ahead is feasible using the loglinear models for three-dimensional contingency tables. Knowing the hydrological drought

class values or meteorological drought class for two precedent months, it is possible to make reliable predictions for hydrological drought class in the two following months.

Only for a few cases, the predicted and the actual drought classes were not in agreement. Often, this happens when the values of drought indices are near the upper or lower boundary of the class and easy change to the nearby class when the precipitation deficit or runoff deficit increases or higher precipitation or runoff occurs. The predictions show a lag relative to the observed drought classes when the observed drought classes change suddenly. The results show that hydrological drought predictions for 1 month lead are more accurate by SRI time series than by SPI time series, while for 2 month lead, the prediction results are better by SPI time series.

Some of the inaccuracy may be caused by the concept of meteorological and hydrological droughts and the two indices we selected. Some joint drought indices have been developed by using SPI or SRI values of different time scales indicating meteorological and hydrological droughts (Kao and Govindaraju 2010), and by joint precipitation and soil moisture to indicate agricultural drought (Hao and AghaKouchak 2013). They were confirmed to identify the onset, persistence and termination of droughts reasonably. Besides, the drought class classification is another control factor resulting in the inaccuracy of hydrological drought predictions. If the boundaries of SPI and SRI in Table 2 change, the drought classes derived from SPI and SRI time series change accordingly, which will cause changes in the parameters of the loglinear models.

Since there are large numbers of parameters in loglinear models for three-dimensional contingency, loglinear modeling for prediction more than 2 month lead time will increase the number of parameters and make the loglinear model more complicated. Hence, it is not foreseen to use loglinear models to increase the lead time of predictions (Moreira, et al. 2008). The results will provide significant information to water resources managers making decisions on drought mitigation measures 1 and 2 month ahead.

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