Stochastic forecasting of agricultural drought based on Palmer Drought Severity Index (PDSI)

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Introduction

Agricultural drought has been defined as an interval of time, generally of the order of months or years when the moisture supply of a region consistently falls below the climatically appropriate moisture supply such that crop production or range productivity is adversely affected which can be expressed by the so-called drought indices. It is not possible to avoid droughts. But drought preparedness can be developed and drought impacts can be managed. Drought forecasting displays a significant role in the mitigation of impacts of drought on water resources systems. Owing to the randomness of the factors responsible for the occurrence and severity of drought, it can be considered as a stochastic process. Time-series forecasting algorithms employing the concept of ARIMA models have been used for short-term forecasting.

Palmer drought severity index (PDSI)

The PDSI is probably still one of the most complex drought indices in use today and it is also one of the few that allows a direct comparison of index values between different climatological regions. Three positive characteristics of the Palmer Index that contribute to its popularity: (1) it provides decision makers with a measurement of the abnormality of recent weather for a region; (2) it provides an opportunity to place current conditions in historical perspective; and (3) it provides spatial and temporal representations of historical droughts. In this study the PDSI computation was done based on Ansari et al., 2008 and Szalai et al., 1998 for Mashhad region in Khorasn-Razavi province in Iran. The mean annual rainfall of this semi-arid region is around 270 millimeter per year.

Seasonal ARIMA model & Time-series analysis

Box et al. (1994) have generalized the ARIMA model to deal with seasonality, and define a general multiplicative seasonal ARIMA model, which are commonly known as SARIMA models. An inherent advantage of the SARIMA models is that few model parameters are required for describing time series which exhibit non-stationary both within and across seasons. Briefly, the SARIMA model can be explained as 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.

$$\phi_p(B)\Phi_p(B^S)\nabla^d\nabla_S^D z_t = \theta_q(B)\Theta_Q(B^S)a_t \qquad (1)$$

where p is the order of non-seasonal auto-regression, d is the number of regular differencing, q is the order of non-seasonal MA, P is the order of seasonal auto-regression, D is the number of seasonal differencing, Q is the order of seasonal MA, s is the length of season, seasonal AR parameter of order P, seasonal MA parameter of order Q.

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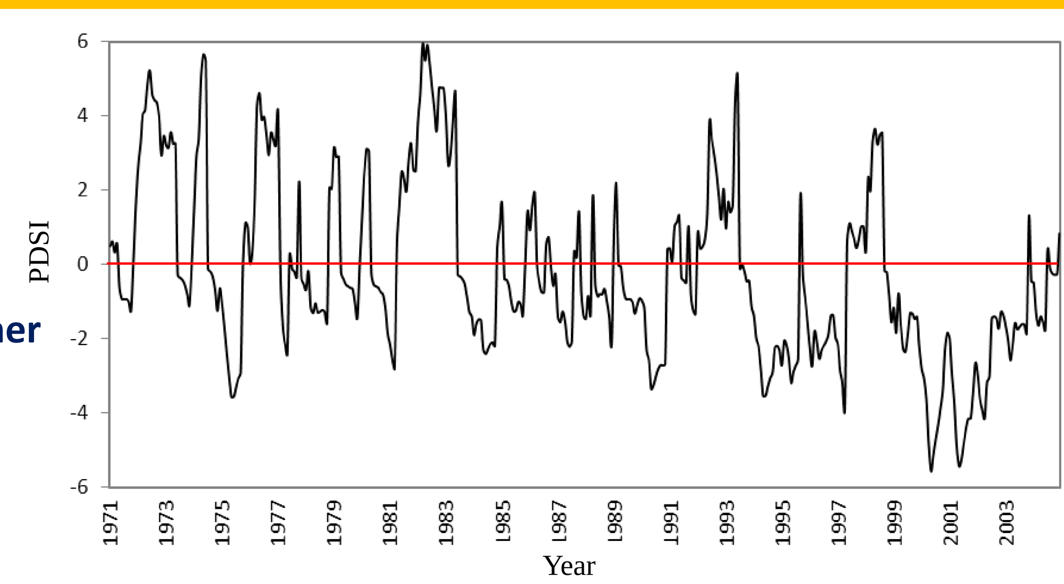
The time series modeling approach involves the following three steps:1) Model identification which includes transforming the data (if necessary) and determining form of the model to be estimated by using autocorrelation function (ACF) and partial autocorrelation function (PACF) functions. 2) Parameter estimation and 3) Diagnostic checking in which the models is performed to reveal possible model inadequacies by analyzing the residuals.

Temporal characteristics of droughts

Fig. 1. The computed PDSI for Mashhad weather station



The time series of PDSI for Mashhad weather station show that the region experienced frequent moderate and severe droughts for all months of the year. Analysis of drought monitoring during the 34 years of PDSI indicated that almost in all years we faced with drought months. The most sever of drought was happened in 2000. Furthermore, more than 64% of months were drought. Among of these droughts the longest drought period was started in September 1998 until November 2003, it means we had more than 5 drought years. Unfortunately, results showed that in the recent decades the frequency of droughts was increased. Therefore it is important to consider this phenomena for agricultural management in the region.

Model development

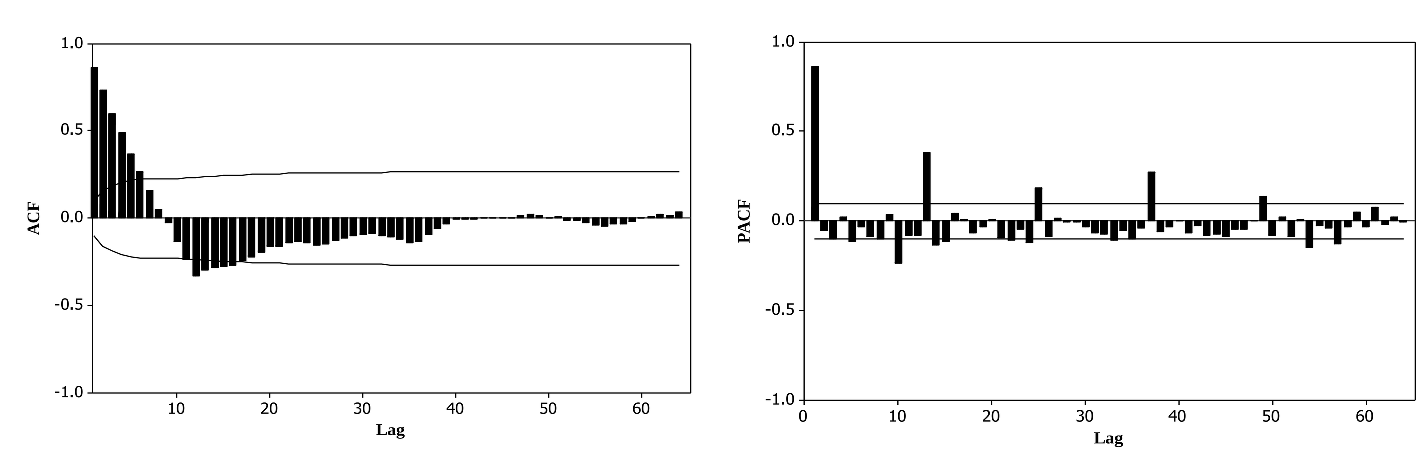


Fig. 2. ACF and PACF plots used for selection of candidate models

In the PDSI time series, the ACF curve decays with mixture of sine and exponential curve and the PACF has a significant spike at lag 1 which suggests AR process (Fig. 2). In the PACF, the significant spike at lag 1 explains how many AR terms needed to explain the autocorrelation pattern in the PDSI time series. This indicates an AR (1) as non-seasonal part of model. The significant seasonal spikes at lags 12 and 24 and 36 in the PACF indicate a SARIMA model.

Using minimum AIC and SBC criteria, the best model out of different candidate models is identified (Table not shown). Finally, the SARIMA(1,0,0)(0,1,1) was selected among five candidate model. Then the estimated parameters of the function are calculated simultaneously for AR and MA parameters. Several tests were employed for diagnostic check to determine whether the residuals of the selected model are independent, homoscedastic and normally distributed.

Drought forecasting

Table. 1. Comparison of statistical properties of the predicted and observed data

Mean observe	Mean forecasted	|z|<1.96	Variance observe	Variance forecasted	Fc<Ftab
-0.24	-0.33	0.35	4.81	5.12	1.15<1.44

Table. 2. The correlation coefficients (R) between observed and predicted data for different lead-times

1-month lead time	2-month lead time	3-month lead time	4-month lead time	5-month lead time	6-month lead time
0.87	0.71	0.24	0.10	0.12	0.12

The one-step-ahead (1-month lead time) predictions of the models as well as the values for the Z-test and F-test are computed for the estimation and validation data sets are shown Table 1, respectively. The data set from 2003 to 2004 is used for validating model for the PDSI. Table 1 introduces basic statistical properties of the observed and predicted data for 1-month lead time. Table 2 presents the correlation coefficients (R) between the observed and predicted data for different lead-times. The predictions are calculated for 1-month lead time to 6-month lead time.

Table 2 indicates that for a longer lead time, the correlation coefficients between the observed and predicted data decrease. Therefore the selected best models from SARIMA building approach using a time series data of PDSI series can be used for the reasonable drought forecasting up to 2 month lead time.

Conclusion

Due to the random nature of contributing factors, occurrence and severity of droughts can be treated as stochastic in nature. Early indication of possible drought can help to set out drought mitigation strategies and measures in advance. In this study, drought durations was simulated by application of linear stochastic models for agriculture drought forecasting based on Palmer Drought Severity Index (PDSI) in Mashhad, Khorasan-Razavi province Iran. Temporal characteristics of droughts based on PDSI as an indicator of drought severity indicated that the region is affected by severe and more or less prolonged periods of drought from 1971 to 2004. Results show that more than 64% months were drought and also in the recent years, duration and severity of drought are increased. A SARIMA model developed to predict drought found to give acceptable results up to 2 months ahead.

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References

Ansari, H., Davary, K and Sanaie, SH. (2008). Drought monitoring based on PDSI index, Khorasn province. Water and soil jo. 22(2). 225-233 (in Persian)

Box, G.E.P., Jenkins, G.M. and Reinsel, G.C. (1994) Time Series Analysis, Forecasting and Control (3rd edn). Prentice-Hall, Englewood Cliffs, NJ.

Mishra AK and Desai VR (2005) Drought forecasting using stochastic models. Stoch Environ Res Risk Assess 19(2): 326-339.

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