International Journal of Plant Production 10 (4), October 2016
ISSN: 1735-6814 (Print), 1735-8043 (Online)
www.ijpp.info

GUASNR

A Bayesian decision model for drought management in rainfed wheat farms of North East Iran

A. Sadoddin[a,*], M. Shahabi[b], V.B. Sheikh[a]

[a]*Associate Professor, Watershed Management Department, Gorgan University of Agricultural Sciences and Natural Resources, Gorgan, Iran.*
[b]*Post Graduate Student, Arid zone Management Department, Gorgan University of Agricultural Sciences and Natural Resources, Gorgan, Iran.*
*Corresponding author. E-mail: amir.sadoddin@gau.ac.ir

Received 21 December 2015; Accepted after revision 4 June 2016; Published online 10 August 2016

Abstract

Drought is a feature of climate that can occur in virtually all climates. Therefore, it is an inevitable global but site-specific phenomenon which requires tools to predict and strategies and options to cope with it. In this research, the ability and effectiveness of the Bayesian Decision Networks (BDNs) approach in decision-making and evaluating drought management options for rainfed wheat production in the eastern region of Golestan Province, Iran are demonstrated. The results revealed that during drought conditions, the Koohdasht cultivar had higher yield than other cultivars of wheat. Two management scenarios have been specified for the forecasted period on the basis of wheat cultivars adopted in the region. The results of scenario analysis with a BDN model indicate that the probability of low, medium and high yield levels in scenario 2 (Koohdasht 70%, Zagros 20% and the other cultivars 10%) has a better status compared with scenario 1 (current condition). The paired t- test indicates that there is a significant difference between the two scenarios for wheat yield in low and medium states ($P<0.05$). Adopting appropriate cultivars in the region with favourable yield and adaptability to drought conditions proved to be an effective management action. The BDN approach implemented in this research serves as a valuable tool to represent the system as a whole, to integrate outputs from models and expert judgment, to evaluate the outcomes necessary for decision-making and to communicate uncertainty of the parameters in the model.

Keywords: Agricultural drought; Bayesian decision model; SARIMA; Management scenarios; Rainfed wheat; Golestan Province.

Introduction

For countries situated in arid regions such as Iran, the characterisation of drought has become increasingly important to environmental management. Drought is an extended period of time when a region experiences a deficiency in water supply. It can have substantial impacts on the ecosystem and agriculture of the affected region (Palmer, 1965). Climate change is very likely to affect the frequency and intensity of extreme events such as droughts and floods. Future climate change can be projected by global climate models such as General Circulation Model (GCM) (IPCC, 2001). Koocheki et al. (2006) used the UKMO[1] model to anticipate the climate change and agro-climatic

1- United Kingdom Meteorological Organization indicators for 25 meteorological stations in Iran. The UKMO model predicted an increase in temperature up to 2.7 °C and a reduction in rainfall up to 12% by 2050. In recent years, frequent and severe droughts have incurred extensive damages to the environment and agricultural sector and it is anticipated to worsen in future due to climate change. Roshan and Grab (2012) reported that water deficit during growing season of winter wheat producing areas of Iran will increase from 5.2% in 1980 to over 23% by 2050 and 38% by 2100.As a result, the death toll of livestock and wildlife was unprecedented.

Agricultural drought occurs when there is not sufficient soil moisture content to meet the needs of a particular crop for a specific period of time. Agricultural drought is a difficult concept to characterise as it involves not only the range of water deficiency in the whole system, but also water shortage in relation to plant water demand. The water demand of a crop, in turn, depends on its variety, state and stage of growth (Webster, 1978).

In this paper, an approach for the development and application of a Bayesian Decision Network (BDN) model for agricultural drought management is described. BDN models, which come from a marriage between probability theory and graph theory (Jordan, 2004), provide remarkable features to deal with both the complexity of natural systems and with the need to support the decision making process despite scientific uncertainty and a lack of data and knowledge (Borsuk, 2001). Being a graphical model, BDN structures the problem based on a conceptual model framework assigned to the system, so it is visually interpretable by stakeholders and decision-makers (Ames et al., 2005). In addition, as results are presented in a probability context, BDNs give an explicit representation of uncertainty (Bromley, 2005). The BDN analysis includes a graphical model of some linked key variables in a system associated with conditional probability distributions derived from a variety of data and information. BDNs have been applied to a variety of natural resource management issues. For example, Dorner et al. (2007) employed a BDN to assess the impacts of agricultural non-point source pollution on a catchment scale. Sadoddin et al. (2005) developed a catchment-scale BDN to assess the ecological impacts of dryland salinity. Water resource management and stakeholder involvement in decision making were the focus of projects described in Bromley et al. (2005) and Hendriksen et al. (2007). Sadoddin (2010) using BDNs predicted the socio-economic and biophysical impacts of biological scenarios for salinity management for the Little River Catchment in NSW, Australia. The aim of this paper is to demonstrate a Bayesian decision model as an integrated approach for agricultural drought management in the east of Golestan Province, where it is one of the main areas of wheat production as a staple food in Iran. The model is used to: 1) estimate the probability of agricultural drought occurrence in the east of the Golestan Province and 2) estimate the probability of changes of farmers' income from wheat cultivars under two management scenarios.

Materials and Methods

Description of study area

Golestan Province is located in the northeast of Iran. It has an area of about 20,378 km^2 and geographically lies between 53° 50' and 56° 18' East longitude and 36° 25' and 38° 08' Northlatitude. More than 90% of crops cultivated in this province are wheat, barley, rice, cotton and soybean. About 83% of rainfed wheat farmlands are spread over eastern parts of the province within the political boundaries of four townships, Gonbad, Kalaleh, Minoodasht and Azadshahr (see Figure 1 and Figure 2). The dominant wheat cultivars in the study area are Koohdasht, Zagros, LineA, Tajan, Azar 2, Sardari and Niknejad (Rainfed Agriculture Research Institute of Iran, 2004). Mean annual precipitation varies from 252 mm in Til-abad climatology station to 840 mm in Lazoreh station. Mean annual temperature is about 18.2 °C. In order todetermine the drought condition, 10 climatology stations within and in the vicinity of the study area were considered. The locations of the stations are shown in Figure 1.

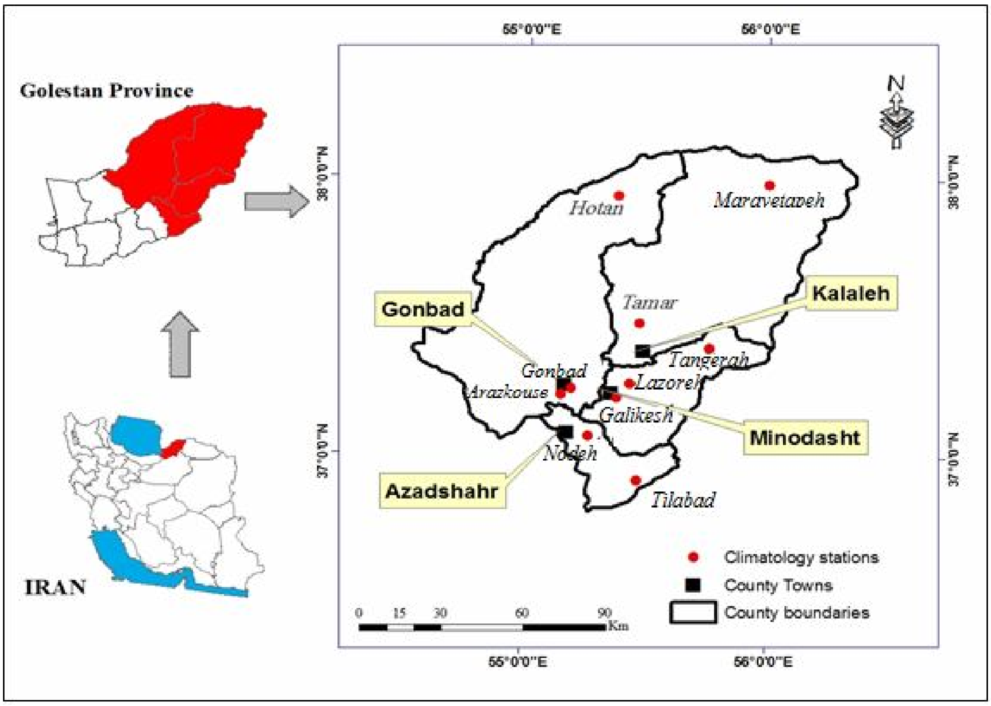

Figure 1. Location of the study area and distribution of climatology stations.

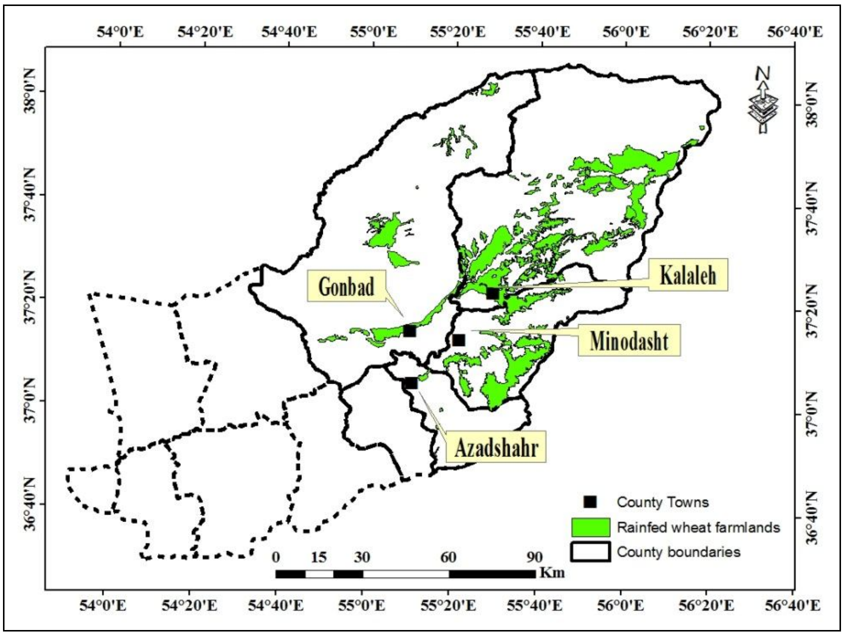

Figure 2. The spatial distribution of rainfed wheat farmlands in the east of Golestan Province.

Model development using a BDN

BDNs can be categorically considered as a fundamental modelling tool for decision-making and management where uncertainty is a key consideration (Sadoddin, 2010). Nodes in the conceptual framework of a BDN represent decision, state, utility or impact variables, while arrows or links between nodes represent conditional probability distributions (Letcher and Weidemann, 2004). Relationships among variables (nodes) are connected by arrows that represent causal dependencies or an aggregate summary of complex associations (Reckhow, 2003).

A key step in model development is the specification of a conceptual framework for the model (Letcher and Weidemann, 2004). A conceptual model is a descriptive model of a system based on quantitative and qualitative assumptions about its elements, variables' interrelationships and system boundaries. It is an aid to conceptualise and investigate the interaction between the linked components of a management system. Figure 3 shows the conceptual framework underlying the BDN developed for the agricultural drought management in the east of the Golestan Province. This framework incorporates the variables of agricultural drought in rainfed wheat production.

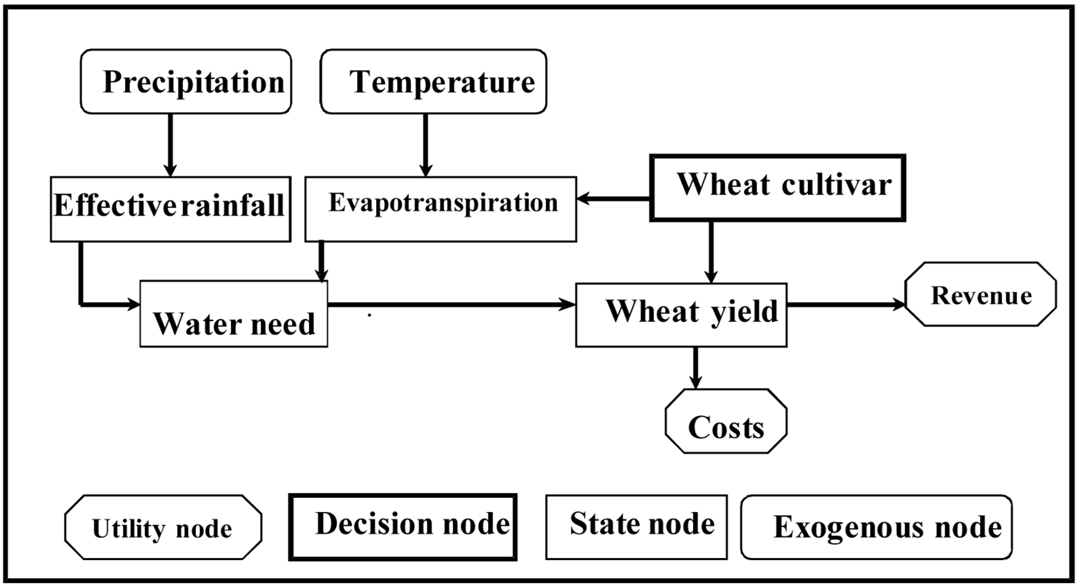

Figure 3. Conceptual model framework for agricultural drought management in the east of Golestan Province.

The BDN model was developed through the following three steps: (1) development of the conceptual model framework, (2) identifying probable management scenarios, (3) quantifying the system parameters in a probabilistic context using Bayes' rule (Baran and Jantunen, 2004). It is easy to define P(A|B) without reference to the joint probability P(A,B) (Equation 1).

$$P(A \mid B) = P(B \mid A) \times P(A) / P(B) \tag{1}$$

Where P(A) is the prior probability of A. It is prior in the sense that it does not take into account any information about variable B; P(A|B) is the conditional probability of A, given B. It is also called the posterior probability because it is derived from or depends upon the specified value of variable B; P(B|A) is the conditional probability of B given A. It is also called the likelihood and P(B) is the prior probability of B and acts as a normalising constant. Conditional probability tables with valuable information can be used in Bayes' rule to make final probabilities of the end node variables in the BDN model.

To estimate the probability of wheat yield during the forecast period, especially during the drought condition, two management scenarios were specified on the basis of wheat cultivar proportions. Scenario 1 refers to the current condition and scenario 2 is defined as the cultivar proportion of Koohdasht 70%, Zagros 20% and the other cultivars 10%.

To quantify the parameters of the BDN model, the following steps were conducted:

- Applying the GCM under the UKMO Scenario to predict the probable impacts of climate change on precipitation and temperature,
- Forecasting the amounts of precipitation and temperature applying a SARIMA model for four years ahead, starting from 2008 and
- Characterising agricultural drought using the FAO Penman-Monteith method and elicitation of expert knowledge.

Time series

A time series is a set of observations that are arranged chronologically. In time series analysis the order of occurrence of observations is crucial. In time series analysis, a variety of different important technical terms are available such as stationarity, periodicity and trend which fall into temporal categories interpreted as a form of statistical equilibrium (Li et al., 2003). For interpretation purposes, it is often useful to plot the autocorrelation function (ACF) against lag time. The main purpose of time series analysis is forecasting the future events using past records (Mishra and Desai, 2005). In order to forecast the agricultural drought, the precipitation and temperature amounts of four years from 2008 onwards have been forecasted using SARIMA model (see Equation 2).

$$\phi_P(B)\phi_p(B^s)\Delta^d \Delta_s^D Z_t = \theta_q(B)\theta_Q(B^s)a_t \tag{2}$$

where p is the non-seasonal autoregressive degree; d is the difference degree; q is the non-seasonal moving average; P is the seasonal auto regressive degree; D is the seasonal difference degree; Q is the seasonal moving average and s is season duration. In order to choose the best SARIMA model, the SARIMA data analysis strategy (Figure 4) was followed.

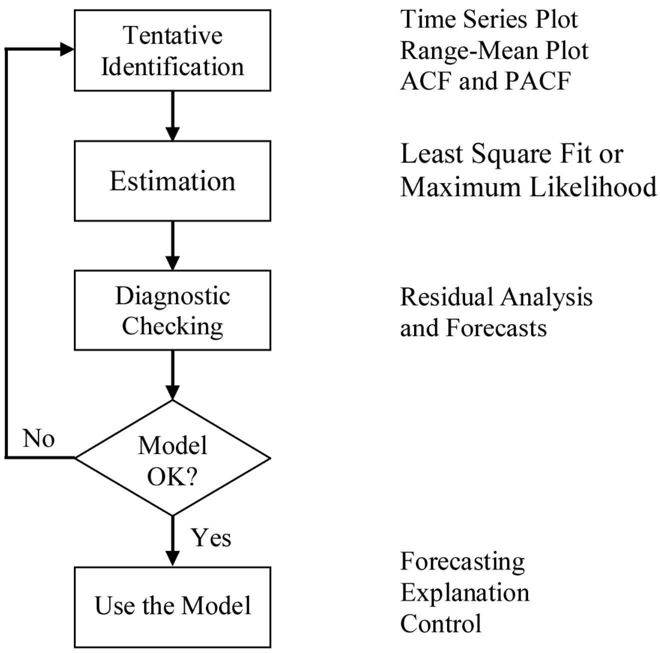

Figure 4. SARIMA data analysis strategy (Source: Meekers, 2004).

The SARIMA model was evaluated with the Nash-Sutcliffe (NS) coefficient (Lhomme, 2004). A value of NS equal to 1 implies that predicted and observed data are in perfect match (Nash and Sutcliffe, 1970). Equation 3 calculates the Nash-Sutcliffe efficiency.

$$C_{NS} = 1 - \Sigma_{i=1}^{n}(Y_{si} - Y_{oi})^2 / \Sigma_{i=1}^{n}(Y_{oi} - \overline{Y_o})^2 \quad (3)$$

where Y_{si} and Y_{oi} are the predicted and observed data, respectively; $\overline{Y_o}$ represents the mean of observed data and n indicates the number of observations.

Calculation of agricultural drought

The FAO Penman-Monteith method was used to calculate the agricultural drought condition (Cai, 2007). This method is similar to the Crop Moisture Index without considering the amount of soil moisture. In this method we have used the amount of effective rainfall instead of precipitation. The FAO Penman-Monteith and Soil Conservation Service methods were used to calculate the potential evapotranspiration and effective rainfall, respectively.

$$ET_o = \frac{0.408\,\Delta(R_n - G) + \gamma\left[890/(T+273)\right]U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34\,U_2)} \quad (4)$$

where ET_o is the reference evapotranspiration (mm day^{-1}); R_n is net radiation at the crop surface (MJ m^{-2} day^{-1}); G is soil heat flux density (MJ m^{-2} day^{-1}); T is mean daily air temperature at 2 m height (°C); U_2 is wind speed at 2 m height (m s^{-1}); e_s is saturation vapour pressure (kPa); e_a is actual vapour pressure (kPa); e_s - e_a is saturation vapour pressure deficit (kPa); D is the slope of vapour pressure curve (kPa $°C^{-1}$) and γ is the psychrometric constant (kPa $°C^{-1}$).

$$Rain_{eff} = f(IR)(1.25Rain^{0.824} - 2.03) \times 10^{0.000955ET} \tag{5}$$

where $Rain_{eff}$ is effective monthly precipitation (mm); *Rain* is monthly precipitation (mm); *ET* is monthly evapotranspiration (mm/period) and *IR* is irrigation depth. The calculations were carried out using CROPWAT software package (Smith, 1992).

Results

SARIMA model

As mentioned earlier, based on ACF and PACF, time series analysis for each meteorological station has been conducted. According to the appropriate P value and minimum mean square error, the best model was chosen. In the next step, the comparison of observed and predicted data was made using the Nash-Sutcliffe coefficient. In most of the meteorological stations, reasonable results were achieved (Table 1 and Table 2). To incorporate the probable climate change impacts into the result, the SARIMA results were adjusted under the UKMO Scenario.

Table 1. The amount of R^2 and NS coefficients for predicted monthly precipitation across different climatology stations.

Climatology station	R^2	NS
Arazkouseh	0.53	0.49
Galikesh	0.29	0.29
Gonbad	0.53	0.52
Lazoreh	0.7	0.69
Nodeh	0.58	0.54
Tangerah	0.48	0.46
Tilabad	0.65	0.51

Table 2. The amount of R^2 and NS coefficients for predicted monthly temperature of Gonbad climatology station.

Station	Variable	R^2	NS
Gonbad	minimum temperature	0.96	0.96
	maximum temperature	0.93	0.93

Based on the results, the correlation coefficients of all stations are significant at a 99% confidence level. According to the Table 1, the best NS coefficient corresponds to the Lazoreh Station with a value of 0.69 and the worst one is related to the Galikesh Station with a value of 0.29. This is on account of a greater variability of precipitation in this station compared to most of the other climatology stations considered in this research. Figures 5 to 8 show the results of SARIMA modelling and the comparison between the observed and predicted data at the Nodeh Station as an example.

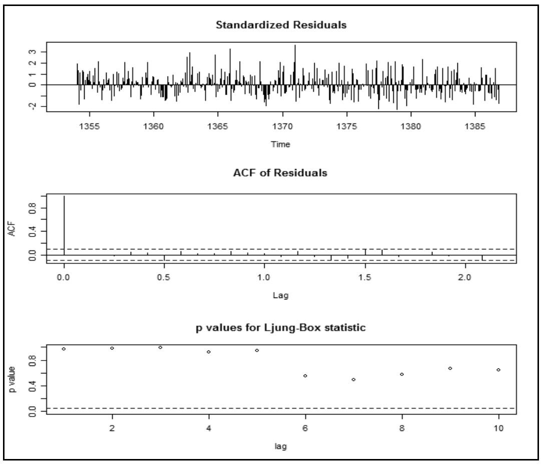

Figure 5. Standardised residuals, ACF of residuals and P value for Ljung-Box statistic for the Nodeh climatology station.

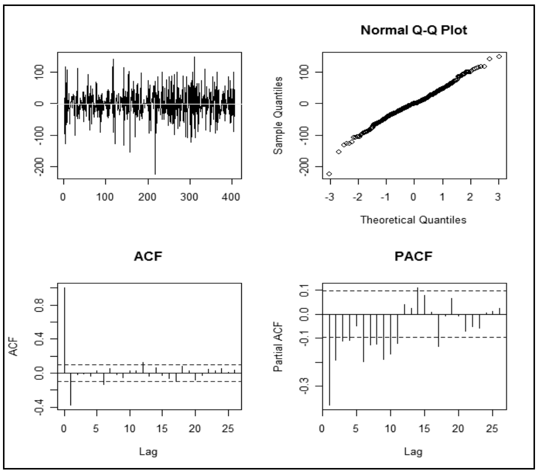

Figure 6. Normal Q-Q, PACF and ACF plots for the Nodeh climatology station.

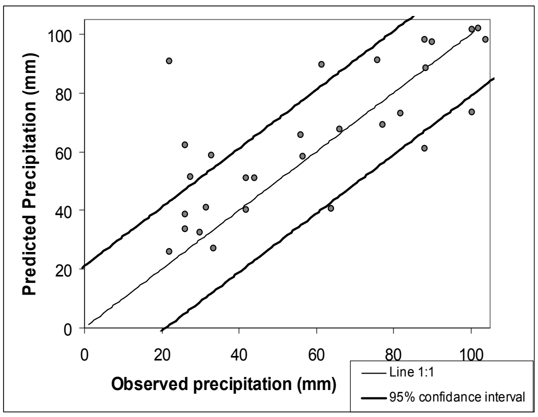

Figure 7. Observed and predicted amount of precipitation distribution in 95% confidence interval for the Nodeh climatology station.

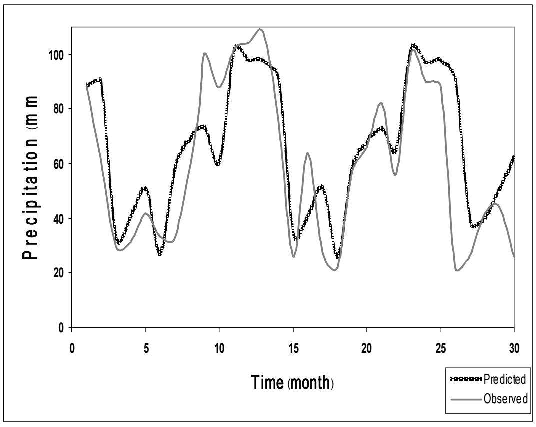

Figure 8. Comparison of SARIMA results versus observed data during evaluation period for the Nodeh climatology station.

Agricultural drought

Using the FAO Penman-Monteith method, the water requirement has been calculated for both the evaluation period (1988 to 2007) based on the observed meteorological data and also for the subsequent four years (2008 to 2011) using the data forecasted by SARIMA model. It should be noted that the forecasted data have been adjusted for climate change scenarios based on UKMO projections. Then, the occurrence probability of different states of agricultural drought for the study area was determined. The occurrence probability of severe and mild drought was calculated to be 19% and 52%, respectively. The occurrence probability of normal condition was considered to be 29%.

Conditional probability tables

The information required to construct the probability table of rainfed wheat yield for the study area was derived from the probability of drought conditions observed in the past and associated wheat yield of various cultivars (Table 3).

Table 3. Conditional probability table of rainfed wheat yield across different drought conditions and wheat cultivars in the east of Golestan Province, Iran.

Drought condition	Wheat cultivars	Wheat yield*		
		Low	Medium	High
Severe	Koohdasht	30.02	44.18	25.8
Severe	Zagros	54.61	39.7	5.69
Severe	Others**	62.5	36.21	1.29
Mild	Koohdasht	29.82	52.25	17.93
Mild	Zagros	44.37	54.17	1.46
Mild	Others	58.2	40.3	1.5
Normal	Koohdasht	5.4	57.86	36.74
Normal	Zagros	8.12	86.9	4.98
Normal	Others	35.1	58.61	6.29

* High yield: more than 3000kg/ha; Medium yield: 2000-3000kg/ha; Low yield: less than 2000kg/ha.
** Line A, Tajan, Azar 2, Sardari and Niknejad wheat cultivars.

Table 4 shows the conditional probability table of agricultural drought under different conditions of evapotranspiration and effective rainfall during the growing season of wheat in the east of Golestan Province.

Table 4. Conditional probability table of agricultural drought under different conditions of evapotranspiration and effective rain during the growing season of wheat in the east of Golestan Province, Iran.

Evapotranspiration condition*	Effective rain**	Agricultural drought		
		Normal	Mild	Severe
Low	Low	0	75	25
Medium	Low	0	76	24
High	Low	0	57	43
Low	High	100	0	0
Medium	High	90	10	0
High	High	0	0	0

* Evapotranspiration levels: Low < 250 mm/period, Medium: 250-270 mm/period and High: > 270 mm/period.

** Effective rain levels: Low <250 mm and High >250 mm.

Total probability distribution

Using Tables 3 and 4, the total probability distribution of wheat yield was calculated using Bayes' rules under different drought conditions (see Table 5). The analysis indicates that for the mild and normal drought conditions, the probability of occurrence of wheat production at the state of medium is greater than that for the states of low and high. In contrast, the probability of occurrence of wheat production is greater at the state of low in the case of severe drought condition.

Table 5. Total probability distribution of rainfed wheat yield in different drought conditions.

Drought condition	Rainfed wheat yield (percent)		
	Low	Medium	High
Severe	44.96	40.89	14.13
Mild	41.16	49.47	9.3
Normal	14.16	65.27	20.56

As shown in Table 5, the change in the likelihood of the combined Medium and High yield under the drought conditions is sensible. Somewhat similar likelihood of High yield under a severe drought and a normal year has been achieved. This can be justified by the definition of the Medium and High yield in this research.

Figure 9 illustrates the system parameters of BDN based on the data recorded in the past, along with the information of Table 5 and the census of agriculture in the study area.

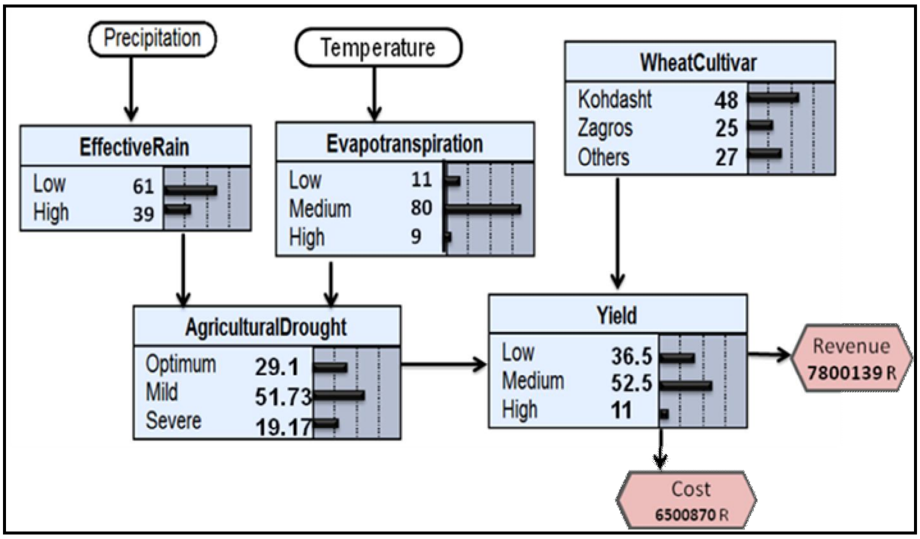

Figure 9. BDN system parameters based on recorded data and census of agriculture in the study area. Costs and revenues are in Iranian Rials per hectare.

The analysis of the status of agricultural droughts based on the BDN framework indicates that during the past two decades, mild and/or severe agricultural droughts have occurred in the east of Golestan Province in about 71% of cases.

The status of agricultural drought forecasted for four years starting from 2008 has been presented in Figure 10. These results support the calculation of probability of drought occurrence using the BDN model under the two scenarios (see Figure 11).

Year	Class Code	Meteorological Stations: Gonbad	Nodeh	Arazkouseh	Lazoreh	Tangerah	Tilabad	Galikesh
2008	0		0					
	1	1		1	1	1		1
	2						2	
2009	0		0					
	1	1		1	1	1		
	2						2	2
2010	0							
	1	1	1		1	1		1
	2			2			2	
2011	0							
	1				1	1		1
	2	2	2	2			2	

Key guide for drought classes

Drought Condition	Class Code
Normal	0
Mild	1
Severe	2

Figure 10. Agricultural drought classes forecasted between 2008 and 2011 at climatology stations located in the study area.

The results of scenario analysis indicate that scenario 2 (Koohdasht 70%, Zagros 20% and the other cultivars 10%) shows a better performance than scenario 1 (the current condition) in terms of crop yield.

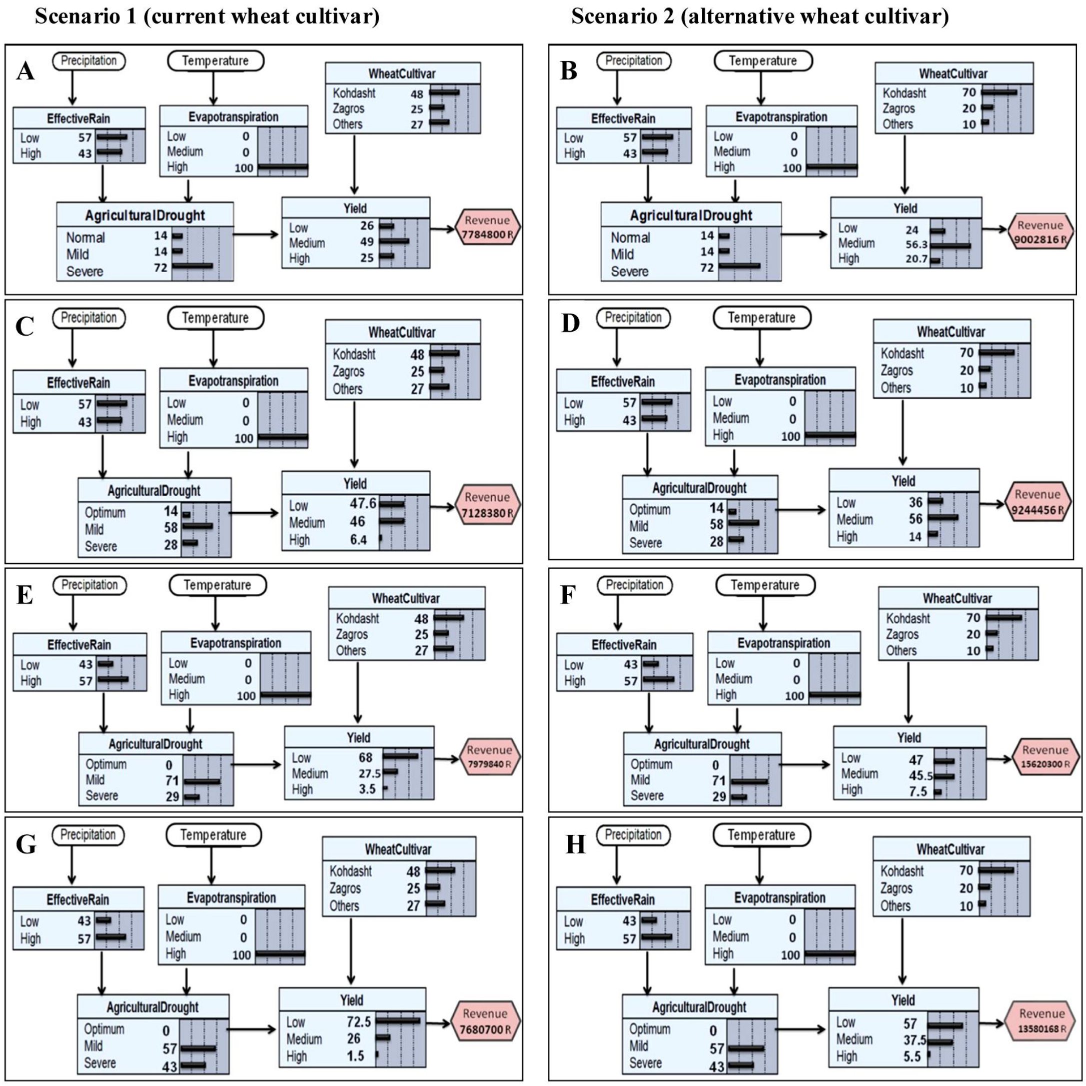

Figure 11. BDN parameters of: A) Scenario 1 based on forecasted variables for 2008; B) Scenario 2 based on forecasted variables for 2008; C) Scenario 1 based on forecasted variables for 2009; D) Scenario 2 based on forecasted variables for 2009; E) Scenario 1 based on forecasted variables for 2010; F) Scenario 2 based on forecasted variables for 2010; G) Scenario 1 based on forecasted variables for 2011; H) Scenario 2 based on forecasted variables for 2011.

Discussion and Conclusions

Natural resources management deals with complex and heterogeneous issues. There is often a paucity of information about one or more processes involved in natural systems. Models that rely on data alone (e.g. traditional deterministic or process models) are not suitable to assess uncertain processes in the system. BDNs provide a way to overcome data limitations by incorporating input data from different sources. Therefore, BDNs are considered as useful tools for addressing uncertainty in data as well as for combining data, model simulation and expert knowledge (Uusitalo, 2007).

In this study, the Bayesian decision modelling approach as an integrative management tool has been applied to predict the outcome of implementing different wheat cultivars in order to reduce the consequences of agricultural drought conditions on crop yield as well as on farm income. The results of this study indicate that the SARIMA model was capable of forecasting the amount of monthly precipitation. However, the SARIMA model forecasted the monthly temperature more precisely than monthly precipitation values. The application of the UKMO climate change scenarios in the analysis did not produce a statistically significant difference in the results of SARIMA forecasts for the period of 2008 to 2011. This is mainly due to the short length of the project period (IPCC, 2001). The analyses indicate that the probability of drought occurrence is higher than normal condition in the study area. Therefore, it is crucial to consider the water demand of different varieties of wheat, as a strategic agricultural product, particularly during drought conditions. As discussed earlier, in this study two scenarios with different combination of wheat cultivars with various water requirement have been developed and their outcomes in terms of crop yield and revenue with respect to different drought condition have been investigated. The analysis revealed that there is a significant difference between the two scenarios with respect to crop yield for the low and medium states of yield variable in the BDN network ($P<0.05$). However, in case of the high state of yield variable there is no a significant difference between the two scenarios. This indicates that under drought conditions in the study area, it is still possible to reduce the impacts of agricultural drought by planting wheat varieties which are more tolerant to the drought conditions. The research outcomes also suggest that there is a need to introduce and/or encourage the use of Koohdasht cultivar through extension practices among the farmers in eastern parts of Golestan Province. This can be achieved without any financial hurdle on farmer communities and local authorities. The social and cultural attitudes of farmers play a major role in the success of the extension practices which should be considered in the study area. Any success in this regard will lead to an economic improvement among the farmers which are mainly dependent on wheat yield.

However, this research does not provide the ultimate answers to agricultural drought problems, given the limitations of the data and information about actual drought management and its various consequences. When new data on the outcomes of drought management options are received, the state of the entire system can be updated, leading to ongoing improvements in the models capacities. To achieve an actual agricultural drought management, some other driving factors such as cropping calendar and supplemental irrigation should be incorporated in the modelling process.

As with any other model, a Bayesian decision network is a finite representation of a complex world based on a set of assumptions. A key strength of a Bayesian decision network is the transparency of assumptions. This allows its users to identify the information included in the model, as well as the information excluded from the model (Rasmussen et al., 2012).

The development of a decision analysis tool using the BDN approach for the study area has addressed the need for an integrated approach arising from the nature of environmental management, in general and management of agricultural drought in the area, in particular. The BDN approach implemented in this research serves as a valuable tool to represent the system as a whole, to integrate outputs from models and expert judgment, to evaluate the outcomes necessary for decision-making and to communicate uncertainty of the parameters in the BDN model.

Acknowledgements

The authors are pleased to express their sincere gratitude to Dr. Lachlan Newham and Dr. Felix Andrews for their invaluable insights into this research. We also wish to thank Dr. Bairam Komaki and the anonymous reviewers for their very useful comments. The research was funded by the Ministry of Sciences, Research and Technology of Iran through Gorgan University of Agricultural Sciences and Natural Resources.

References

Ames, D.P., Neilson, B.T., Stevens, D.K., Lall, U., 2005. Using Bayesian networks to model watershed management decisions: an East Canyon Creek case study. J. Hydroinf. 7, 267-282.

Baran, E., Jantunen, T., 2004. Stakeholder consultation for Bayesian decision support systems in environmental management. Regional Conference on Ecological and Environmental Modelling (ECOMOD), Penang, Malaysia, pp. 1-7.

Borsuk, M., Stow, C., Higdon, D., Reckhow, K., 2001. A Bayesian hierarchical model to predict benthic oxygen demand from organic matter loading in estuaries and coastal zones. Ecol. Modell. 143, 165-181.

Bromley, J., Jackson. N., Clymer,O., Giacomello, A., Jensen, F., 2005. The use of Hugin to develop Bayesian networks as an aid to integrated water resource planning. Environ. Modell. Softw. 20, 231-239.

Cai, J., Lio, Y., Lei, T., Pereira, L., 2007. Estimating reference evapotranspiration with the FAO Penman–Monteithequation using daily weather forecast messages. Agri. Forest Meteorol. 145 (1-2), 22-35.

Dorner, S., Shi, J., Swayne, D., 2007. Multi-objective modelling and decision support using a Bayesian network approximation to a non-point source pollution model. Environ. Modell. Softw. 22, 211-222.

Henriksen, H.J., Rasmussen, P., Brandt, G., Von Bülow, D., Jensen, F.V., 2007. Public participation modelling using Bayesian networks in management of groundwater contamination. Environ. Modell. Softw. 22, 1101-1113.

IPCC., 2001. In: Watson, R.T., Zinyowera, M.C., Moss, R.H., Dokken, D.J.(Wds)., Special report on the regional impact of climate change, an assessment of vulnerability. Cambridge University Press, the UK.

Jordan, M., 2004. Graphical models. Stat. Sci. 19 (1), 140-155.

Koocheki, A., Nasiri, M., Kamali, G.A., Shahandeh, H., 2006. Potential impact of climate change on agro-climatic indicators in Iran. Arid Land Res. Manag. 20, 245-259.

Letcher, R.A., Weidemann, S., 2004. Modelling economic-ecological impacts in NSW coastal catchments- feasibility study. iCAMClient Report.

Lhomme, J., Bouvier, C., Perrin, J.L., 2004. Applying a GIS-based geomorphological routing model in urban catchments. J. Hydrol. 299, 203-216.

Li, Y., Campbella, E.P., Haswell, D., Sneeuwjagt, R.J., Venables, W.N., 2003. Statistical forecasting of soil dryness index in the southwest Australian Forest Ecol. Manag. 183, 147-157.

Meekers, W.Q., 2004. Class notes for Statistics 451: applied time series. Iowa State University.

Mishra, A.K., Desai, V.R., 2005. Drought forecasting using stochastic models. Stoch. Env. Res. Risk A. (SERRA). 19 (5), 326-339.

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I: A discussion of principles. J. Hydrol. 10 (3), 282-290.

Palmer, W.C., 1965. Meteorological drought, Research Paper No. 45, Washington, D.C: U.S. Weather Bureau.

Rainfed Research Institute of Iran, 2004. Technical guideline for rainfed wheat. 50p.

Reckhow, K.H., 2003. Bayesian approaches in ecological analysis and modelling. In: C.D. Canham, J.J. Cole, W.K. Lauenroth (Eds.) Models in ecosystem science. Princeton University Press.

Roshan, Gh.R., Grab, S.W., 2012. Regional climate change scenarios and their impacts on water requirements for wheat production in Iran. J. Plant Prod. 6 (2), 239-266.

Sadoddin, A., Letcher, R.A., Jackeman, A.J., Newham, L.T.H., 2005. A Bayesian decision network approach for assessing the ecological impact of salinity management. Math. Comput. Simulat. 69, 162-167.

Sadoddin, A., 2010. Bayesian network models for integrated catchment-scale management of salinity. LAP LAMBERT Academic Publishing. Germany.

Smith, M., 1992. CROPWAT- A computer program for irrigation planning and management. FAO Irrigation and Drainage Paper 46.

Uusitalo, L., 2007. Advantages and challenges of Bayesian networks in environmental modelling. Ecol. Modell. 203 (3-4), 312-318.

Webster, N., 1978. Webster's new twentieth century dictionary. World Pub. Co. Inc. USA.