European Water 57: 367-374, 2017.

Ground water risk management using dynamic bayesian networks and PROMETHEE method

A. Roozbahani*, E. Ebrahimi and M.E. Banihabib
Department of Irrigation and Drainage Engineering, College of Aburaihan, University of Tehran, Iran
* *e-mail: roozbahany@ut.ac.ir*

Abstract: The aquifers are considered as the best and most accessible source of fresh water. In recent years, they have been faced with severe water withdrawal in Iran, therefore some plains was considered as forbidden plains that it means the water withdrawal from these aquifers is unauthorized. Given such a critical situation in aquifers, the need for management of groundwater resources in the form of tools such as monitoring the level of the aquifers and developing the restoring scenarios is essential. Then for this purpose, A Decision Support System-DSS has been developed in this paper based on Prediction of groundwater level and Multi Criteria Decision Making methods (MCDM). Due to the flexible and simple structure, a probabilistic Dynamic Bayesian Networks (DBNs) has been used for monthly groundwater level prediction under uncertainties. After analyzing the obtained results, some applicable groundwater management scenarios such as artificial recharge and irrigation system change as well as relative criteria such as economic, social and technical attributes have been defined for decision making procedure. After elicitation of decision makers' opinions about criteria's relative importance and performance, among the MCDM methods, PROMETHEE-II technique has been applied to ranking the scenarios regarding their efficiency in restoring the Birjand aquifer in Iran which has a critical groundwater resource condition. The results show the ability of the proposed DSS in planning and management of groundwater resources, reducing the risk of aquifer level declining by applying short term management scenarios and predict its effects on rehabilitation.

Key words: Bayesian Networks, Groundwater Management, MCDM, PROMETHEE-II, DSS

1. INTRODUCTION

The water crisis affects the aquifers and made critical situation in most of the countries in arid and semi-arid regions especially in Iran. Although aquifers contain low percentage of water on the earth, but often have fresh water resources and high quality and access to them is as easy as possible that this could lead to a massive water withdrawal from the country's aquifers and groundwater levels are falling. As a result, some plain was considered as forbidden plains that it means the water withdrawal from these aquifers is unauthorized and illegal that has made the serious tensions in water management. Birjand plain as one of the banned plains in Iran, in recent years has been faced with a sharp drop in groundwater level, which requires management practices by integrating predictive tools such as Bayesian Networks (BN); a tool with which we can improve the effectiveness of the proposed management scenarios to predict the aquifer water level. Management scenarios could include reducing water withdrawals from the aquifer, preventing unauthorized wells and so on.

Given the critical situation of water resources and lack of efficiency in removing all stress management scenarios in Birjand, the need to apply Multi Criteria Decision Making (MCDM) in this area is necessary. In fact by using these methods, depending on socioeconomic status and geographical nature of the region, the best management scenario can be proposed. Therefore, in this study, the practical scenarios will be used to remove water stress in Birjand and by applying Dynamic Bayesian Network (DBN) tools, impacts of management scenarios on improving groundwater will be investigated and risk management will be performed on the plain.

It is important to mention that in the recent years, due to the flexible and simple structure, Bayesian Networks has been used in different water related problems, especially about the hydrological predictions. Many researchers use it to better understand and model the complex issues of artificial intelligence (Charniak, 1991; Heckerman et al., 1995; Jensen, 1996), groundwater management (Henriksen et al., 2007; Olalla et al., 2007; Farmani et al., 2009), irrigation and agricultural systems modeling (Batchelor and Cain, 1999), integrated natural resource management (Borsuk et al., 2004; Hamilton et al., 2007; Johnson et al., 2009; Alameddine et al., 2010) and river basins modeling (Kragt et al., 2009; Merritt et al., 2010; Holzkämper et al., 2012; Madadgar et al., 2014).

Also a lot of researches have been done in the field of application of MCDM technique in water resources systems. For example, Geng and Wardlaw (2013) applied a MCDM approach in a river basin in China, in order to integrate different purposes in planning, applied management and decision making. In their research a variety of measures based on economic, social and environmental and management scenarios were developed. Compromise planning (CP) based on the distance from the ideal solution was used in the mentioned study. Dabral et al. (2014), using spatial integration and multi criteria decision making, determined the proper locations for artificial recharge of aquifers in India. Azarnivand et al. (2015) presented some strategic options to restore Urmia Lake basin in Iran through the matrix of strength - weakness - opportunity - threat (SWAT) and ranked them by fuzzy analytic hierarchy process (FAHP) based on sustainable development criteria. According to the description provided, the main innovations of the research include:

- Develop a model to predict groundwater level with the help of probabilistic Bayesian Networks
- Develop an integrated decision support system (DSS) based on predicting the future condition with the Dynamic Bayesian Network and taking into account the economic and social parameters for ranking scenarios to help revive the Birjand aquifer in Iran, using a practical MCDM technique, namely, PROMETHEE-II.

2. METHODOLOGY

2.1 Dynamic Bayesian Network

This research is focused on models that belong to the class of probabilistic graphical models, with their one prominent member, Dynamic Bayesian Networks (DBNs) (Dean and Kanazawa, 1989). BNs are widely used practical tools for knowledge representation and reasoning under uncertainty in equilibrium systems. BNs are probabilistic graphical models that offer compact representations of the joint probability distribution over sets of random variables (Molina et al., 2013). A BN consists of three main elements: a set of variables that represent the factors relevant to a particular environmental system or problem; the relationships between these variables that quantify the links between variables and the set of conditional probability tables (CPTs) that quantify the links between variables and are used to calculate the state of nodes. The first two elements form a Bayesian Diagram and the addition of the third forms a full structure. A BN can be run as a standalone network, but it is possible to link together a number of networks to produce an Object-Oriented Bayesian Network (OOBN) model (Koller and Pfeffer, 1997). OOBNs are based on the Object-Oriented Programming paradigm (OOP) and thus adopt the same attributes used in OOP languages. OOBNs can be utilized in two ways. First, they can be used for time slicing for problems in which processes take place over multiple time periods (Kjaerulff, 1995). This is how DBNs are built. Because BNs are not intended for transient analysis, time slicing provides one way to generate predictive simulations. This is the method that has been adopted for the current study where networks representing different time domains are linked to outputs nodes to produce a dynamic probabilistic model for monthly groundwater level prediction.

Figure 1 is an overview of the concept of dynamic Bayesian Networks. DBN model is a stationary Markov process under the influence of components and changes that are repeated over time. A dynamic Bayesian Network is a way to expand of Bayesian Network to model the probability distribution of random variables.

A DBN is defined as a pair of BNs ($B_1, B_{\rightarrow}$), where B_1 is a BN represents the initial distribution of Z_1 and $B_{\rightarrow}$ is two time slice BN (2TBN), that defines the transition distribution $P(Z_t|Z_{t-1})$ using a Directed Acyclic Graph (DAG) as follows (Murphy, 2002):

$$P(Z_t|Z_{t-1}) = \prod_{i=1}^{N} P(Z_t^i|P_a(Z_t^i)) \tag{1}$$

where Z_t^i is ith node in time of t and $P_a(Z_t^i)$ is parent of Z_t^i in the graph.

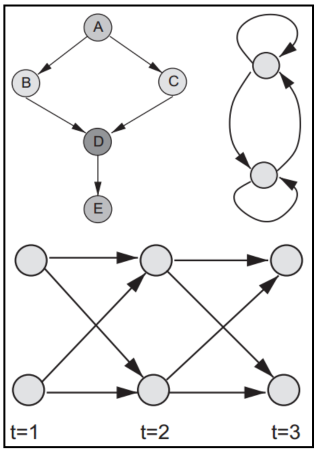

Figure 1. Top left: A simple Bayesian Network. Top right: Network with two feedbacks that they interact with each other; this is not a Bayesian Network. Bottom: time-dependent dynamic Bayesian Networks

2.2 Multi Criteria Decision Making (MCDM)

The first stage in each MCDM problem is to determine the following issues (Roozbahani et al. 2012):

- Identification of the decision makers and stakeholders
- Selection of the criteria and their relative weights
- Selection of the alternatives

After that, selection of a proper method to rank these alternatives is necessary. As it was mentioned before, PROMETHEE-II method has been selected in this paper for purpose of groundwater management. This method has been briefly described in the following section.

2.2.1 PROMETHEE-II

The PROMETHEE family of outranking methods is one of the most recently developed MCDM methods. ROMETHEE is an outranking method for a finite set of alternative actions. It often works based on conflicting criteria. PROMETHEE is also a quite simple ranking method in the concept and application compared with the other methods for multi-criteria analysis (Brans et al., 1986). The implementation of the PROMETHEE II requires the two following additional types of information:

1. The weights of criteria: Determination of the weights is an important step in most multi criteria methods. PROMETHEE II assumes that the decision-maker is able to weight the criteria appropriately, at least when the number of criteria is not too large (Macharis et al., 1998).
2. The preference functions: This function translates the difference between the evaluations of

two alternatives into a preference degree ranging from zero to one for each criterion. To facilitate the association of a preference function to each criterion, the developers of the PROMETHEE method have proposed six types of preference functions which have performed satisfactorily for many real world applications. Each shape depends on up to three thresholds: indifference threshold, preference threshold and gaussian threshold.

The method, which was developed first for single DM case, consists of the following steps:

Step1: Determination of deviations based on pair-wise comparison between each set of two alternatives a and b:

$$d = g_j(a) - g_j(b) \tag{2}$$

where $g_j(a)$ and $g_j(b)$ are the values of criterion j for alternatives a and b, respectively.

Step2: Estimation of preference functions $p_j(a,b)$:

$$p_j(a,b) = H(d_j(a,b)) \tag{3}$$

Step 3: Calculation of an overall or global preference index as follows:

$$\pi(a,b) = \sum_{j=1}^{n} w_j p_j(a,b) \tag{4}$$

where $\pi(a,b)$ varies from 0 to 1 and expresses the degree of which alternative a is preferred over b based on all the criteria (n). w_j is the relative weight of jth criterion.

Step 4: Calculation of outranking flows as follows:

The leaving flow:

$$\varphi^+(a) = \sum_{b \in A} \frac{\pi(a,b)}{n-1} \tag{5}$$

The entering flow:

$$\varphi^-(a) = \sum_{b \in A} \frac{\pi(b,a)}{n-1} \tag{6}$$

Step 5: Calculation of net outranking flow/PROMETHEE II complete ranking as follows:

$$\varphi(a) = \varphi^+(a) - \varphi^-(a) \tag{7}$$

where $\phi(a)$ denotes the net outranking flow for each alternative. A scenario with highest value of net flow represents the best scenario.

3. CASE STUDY AND RESULTS

3.1 Study Area

Birjand catchment basin in the Loot Desert in Iran is located 485 km south of Mashhad and in the East on Iran. The climate is dry and in recent years due to uncontrolled withdrawal of water from aquifers, the region is faced with declining groundwater levels. According to the water level, the average water level drawdown in the Birjand aquifer during last 50 years has been 0.4 meters per year and aquifer deficit volume is about 10.75 million cubic meters. The general direction of groundwater flow, from East to West and from the north and south sides toward the center of the aquifer is in progress. Figure 2 shows the study area along the piezometric network.

For DBN modeling regarding the explicit input data, Necessary Path Condition (NPC) method with 5% confidence level as well as Estimation-Maximization(EM) method was conducted for calibration of BN's structure and parameters, respectively. The calibration period includes 12 years of historical data record (1997 to 2008) and validation data includes a period of 5 years (2009 to 2013) with monthly time step. In this paper, six predictors have been used to predict the groundwater level in the next month (WTT): Rainfall (Rain), Temperature (T), Evaporation (ET), Recharge and discharge in the current month as well as groundwater table in the current month (WT). Also by defining 10 different scenarios for sensitivity analysis to predict the groundwater level in the next month, uncertainties related to the effect of predictive parameters have been investigated. The final selected DBN structure has been shown in Fig. 3.

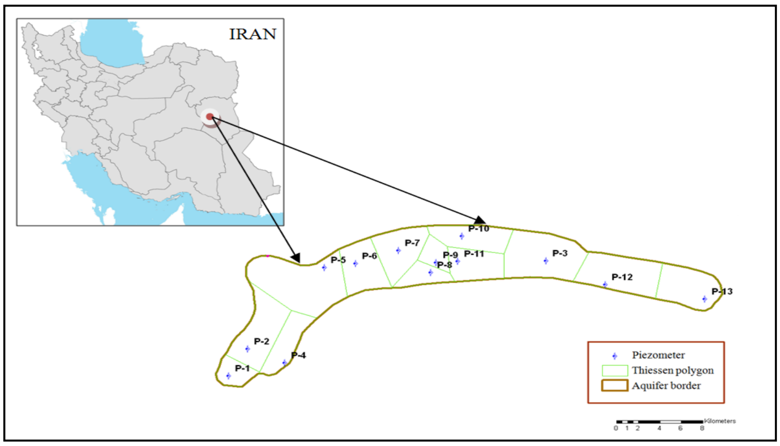

Figure 2. Thiessen network of Birjand aquifer

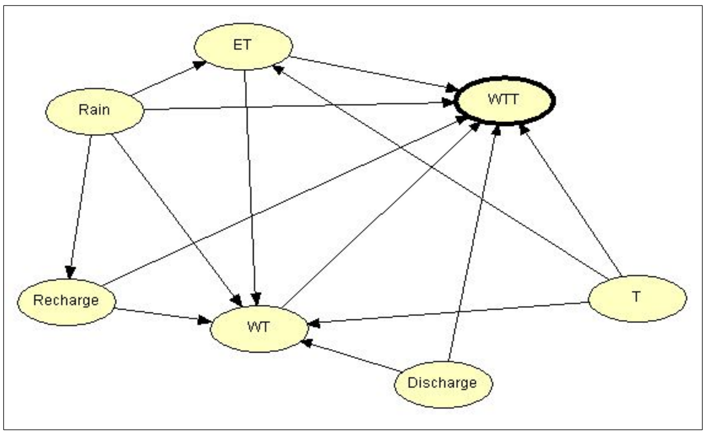

Figure 3. Selected BN structure for groundwater level prediction

Values of the coefficient of determination (R^2) and Root Mean Square Error (RMSE) for superior prediction scenario (Fig. 3) per 13 piezometers were obtained and the accuracy of piezometers is shown in Table 1.

Since groundwater hydrograph is an appropriate tool to evaluate the prediction accuracy, using it, is more desirable to show the efficiency of DBN model. Therefore the amount of groundwater hydrograph was calculated during the five years of validation period. As can be seen in Figure 4, Bayesian Networks has been able to predict with reasonable accuracy.

Table 1. Accuracy of water level prediction in 13 piezometers

Piezometer No.	R^2	RMSE (m)
1	0.12	1.43
2	0.43	0.44
3	0.06	0.41
4	0.97	1.94
5	0.96	2.66
6	0.99	0.77
7	0.99	0.82
8	0.87	0.84
9	0.98	0.63
10	0.98	0.20
11	0.18	3.58
12	0.79	2.09
13	0.16	2.13

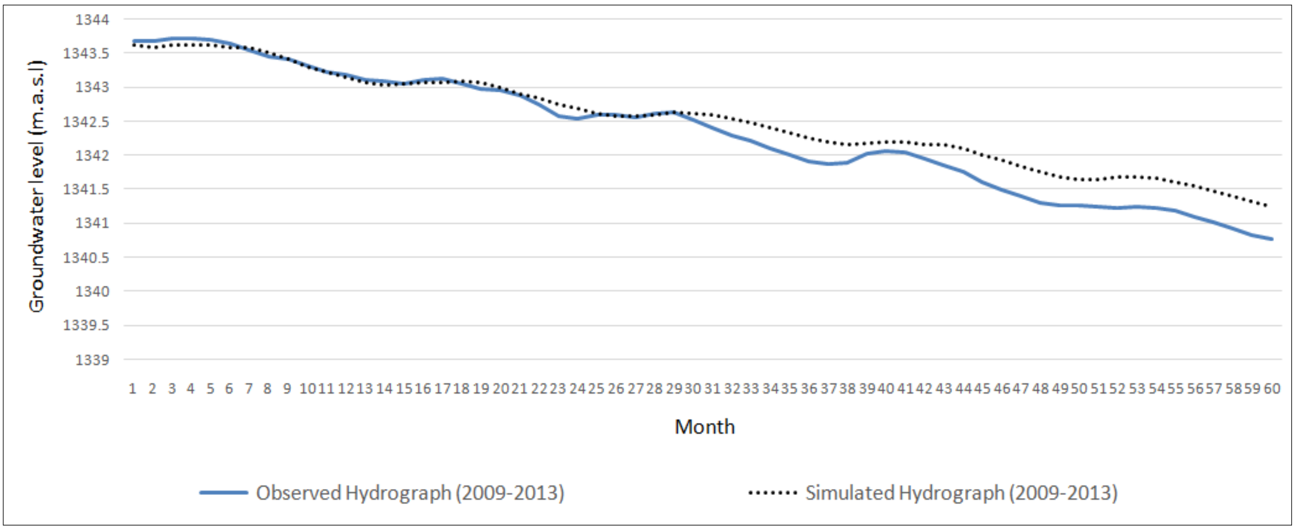

Figure 4. Comparison of observed and predicted groundwater in Birjand plain

3.2 Decision making scenarios for aquifer restoration

The rehabilitation scenarios which are recommended for the plain should suit climatic conditions, geographical potentials of this region and have the operational capability. The scenarios proposed in this research, with research and study and use of the viewpoints of local decision makers in the field of water resources in the study area, were obtained. These scenarios include the following:

S1: Change in surface irrigation to pressurized irrigation systems; S2: Removal of unauthorized wells; S3: Improvement of artificial recharge projects; S4: Installation of smart water meters**.**

3.3 Decision criteria and their values

To conduct the MCDM method, a number of criteria defined in this study based on the existing studies and interview with 20 researchers, professors and decision makers. These criteria have been listed as follows:

C1: Socio-cultural acceptance and participation of stakeholders; C2: Efficiency of applying of scenarios in improvement of the aquifer's water level; C3: Cost of implementation; C4: Ease of implementation. The final decision matrix of the current study is shown in Table 2. In addition, relative weights of four criteria obtained by AHP method (Saaty, 1980) can be seen in this table.

Table 2. Decision matrix of alternative

Scenario	Criteria			
	C1 (w=0.28)	C2 (w=0.30)	C3 (w=0.33)	C4 (w=0.09)
A1	5.7	21	32513	4.9
A2	4.3	12	389	6.7
A3	6.6	21	5400	5.5
A4	5.5	17	16775	5.7

3.4 Data analysis and ranking results

In order to use MCDM method, the precedence orders and preference of criteria have been imposed in the criteria for each decision maker and then their ranking results obtained by PROMETHEE-II, are aggregated to find the group ranking of alternatives. Table 3 shows the final net flows and complete rankings. According the ranking, scenario 3 (artificial recharge projects) and scenario 2 (the removal of unauthorized wells) have obtained the first and second highest ranks, respectively which must be considered by decision makers in short and long term management in this area. The the efficiency of applying of scenario 3 in improvement of groundwater level in the end of 2015 is shown in Figure 5 and compared with the condition that no risk management strategy has been implemented in the study area (current trend continue). As it can be viewed in this figure, this scenario can increase the water level up to 21 cm from current situation.

Table 3. Final ranking results

Rank	Scenario	Net flow
1	S3	0.52
2	S2	-0.07
3	S1	-0.21
4	S4	-0.24

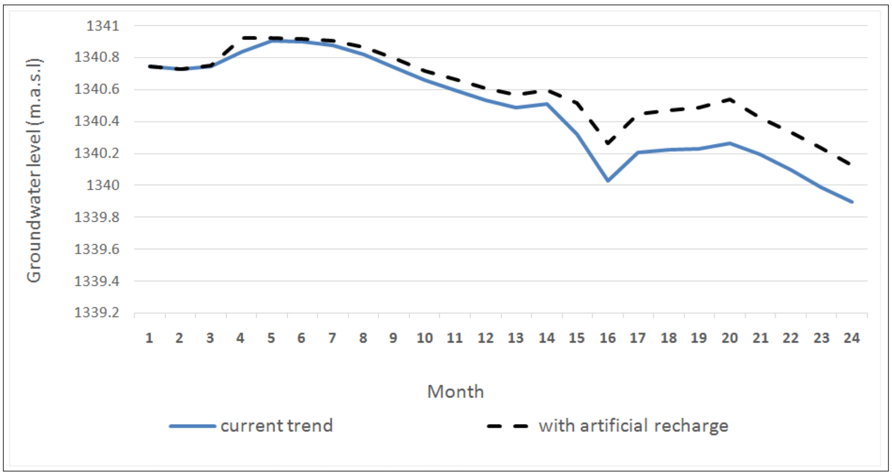

Figure 5. Effect of implementation of selected scenario in groundwater level improvement (2014-2015)

4. CONCLUSION

In this paper, we introduced a comprehensive DSS for groundwater risk management by integration of DBN and MCDM techniques. The capabilities of this framework were evaluated in one of important and under stressed aquifers in Iran. Time dependent Bayesian model which aims to reduce the uncertainty and predict the monthly groundwater level was able to simulate the effects of different management scenarios on improving the groundwater level. To prioritize these scenarios, after presenting the results of the Bayesian Network, four appropriate criteria were determined. Based on these criteria, scenarios were evaluated using PROMETHEE-II as one of the most applicable MCDM techniques. In fact, the decision matrix with four criteria and four scenarios was obtained and then MCDM PROMETHEE method was performed and scenario of optimization of artificial recharge plans was chosen as the best management scenario in the study area. By analyzing the results presented in this study, it is observed that by applying risk management methods and taking into account the conditions prevailing in each region, not only we can obtain the best scenario management, but also the impact of management scenarios on groundwater levels can be easily calculated by DBN rather than existing groundwater models such as MODFLOW. The approach proposed in this study as a Decision Support System, can be utilized by managers and users of water resources systems to reduce water shortage crisis in other similar study areas that are under stressful conditions from water resources point of view.

REFERENCES

Alameddine, I., Cha, Y. K., Reckhow, K. H., 2010. An evaluation of automated structure learning with Bayesian Networks: an application to estuarine chlorophyll dynamics. Environmental Modelling and Software 26: 163–172.

Azarnivand, A., Madani, F.S.H., Banihabib, M.E. 2015. Extended fuzzy analytic hierarchy process approach in water and environmental management (case study: Lake UrmiaBasin,Iran). Environ Earth Sci 73: 13–26.

Batchelor, C., Cain, J., 1999. Application of belief networks to water management studies. Agricultural Water Management 4: 51–57.

Borsuk, M., Stow, C., Reckhow, K., 2004. A Bayesian network of eutrophication models for synthesis, prediction, and uncertainty analysis. Ecological Modelling 173: 219–239.

Brans, J., Vincke, P., Mareschal, B., 1986. How to select and how to rank projects: the PROMETHEE method. European Journal of Operational Research 24(2): 228–238.

Charniak, E., 1991. Bayesian Networks without tears. Artificial Intelligence Magazine 12: 50–63.

Dabral, S., Bhatt B., Joshi, J.P., Sharma, N. 2014. Groundwater suitability recharge zones modelling - A GIS application. ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XL-8: 347-353.

Dean, T., Kanazawa, K., 1989. A model for reasoning about persistence and causation. Computational Intelligence 5 (2): 142–150.

Farmani, R., Henriksen, H.J., Savic, D., 2009. An evolutionary Bayesian belief network methodology for optimum management of groundwater contamination. Environmental Modelling and Software 24: 303–310.

Geng, G., Wardlaw, R., 2013. Application of Multi-Criterion Decision Making Analysis to Integrated Water Resources Management. Water Resour Manage 27: 3191–3207.

Hamilton, G. S., Fielding, F., Chiffings, A. W., Hart, B. T., Johnstone, R. W., Mengersen, K., 2007. Investigating the use of a Bayesian Network to model the risk of Lyngbyamajuscula bloom initiation in Deception Bay, Queensland, Australia. Human and Ecological Risk Assessment: An International Journal 13: 1271–1287.

Heckerman, D., Mamdani, A., Wellman, M., 1995. Real world applications of Bayesian Networks. Communication of the ACM 38: 24–26.

Henriksen, H.J., Rasmussen, P., Brandt, G., Bulow, D.V., Jensen, F.V. 2007. Public participation modelling using Bayesian Networks in management of groundwater contamination. Environmental Modelling and Software 22: 1101–1113.

Holzkämper, A., Kumar, V., Surridge, B. W. J., Paetzold, A., Lerner, D.N., 2012. Bringing diverse knowledge sources together – a meta-model for supporting integrated catchment management. Journal of Environmental Management 96: 116–127.

Jensen, F., 1996. An Introduction to Bayesian Networks. Springer-Verlag D, Heidelberg.

Johnson, S., Fielding, F., Hamilton, G., Mengersen, K., 2009. An integrated Bayesian Network approach to Lyngbya majuscula bloom initiation. Marine Environmental Research 69: 27–37.

Kjaerulff, U., 1995. dHugin: a computational system for dynamic time-sliced Bayesian Networks. Int. J. Forecast 11: 89–111.

Koller, D., Pfeffer, A., 1997. Object-oriented Bayesian Networks. In: Proceedings of the Thirteenth Annual Conference on Uncertainty in Artificial Intelligence UAI-97, Providence, Rhode Island.

Kragt, M. E., Newham, L. T. H., Jakeman, A. J., 2009. A Bayesian Network approach to integrating economic and biophysical modelling.18th World IMACS/MODSIM Congress. 13–17 July, Cairns, Australia.

Macharis, C., Brans, J., Mareschal, B., 1998. The GDSS PROMETHEE procedure: a PROMETHEE-GAIA based procedure for group decision support. Journal of Decision Systems 7: 283–307

Madadgar, S., Moradkhani, H., 2014. Spatio-temporal drought forecasting within Bayesian Networks. Journal of Hydrology 512: 134–146.

Merritt, W. S., Ticehurst, J. L., Pollinoa, C., Fu, B. 2010. The Value of using Bayesian Networks in Environmental Decision Support Systems to support natural resource management. In: International Congress on Environmental Modelling and Software Modelling for Environment’s Sake.5th Biennial Meeting, Ottawa, Canada.

Molina, J. L. Velázquez, D. P. Aróstegui, J. L. G. Velázquez, M.P., 2013. Dynamic Bayesian Networks as a Decision Support tool for assessing Climate Change impacts on highly stressed groundwater systems. Journal of Hydrology 479: 113–129.

Murphy, K. p., 2002. Dynamic Bayesian Networks: Representation, Inference and Learning. PHD.Thesis, University of California, Berkeley, USA.

Olalla, F. M. D. S., Dominguez, A., Ortega, F., Artigao, A., Fabeiro, C., 2007. Bayesian Networks in planning a large aquifer in Eastern Mancha Spain. Environmental Modelling and Software 22: 1089–1100.

Roozbahani, A., Zahraie, B., Tabesh, M., 2012. PROMETHEE with Precedence Order in the Criteria (PPOC) as a New Group Decision Making Aid: An Application in Urban Water Supply Management. Water Resources Management 26(12): 3581-3599.

Saaty, T. L., 1980. The Analytic Hierarchy Process. McGraw-Hill, New York.