Application of Bayesian Decision Networks for groundwater resources management under the conditions of high uncertainty and data scarcity

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Abstract

This paper presents management of groundwater resource using a Bayesian Decision Network (BDN). The Kordkooy region in North East of Iran has been selected as study area. The region has been sub-divided into three zones based on transmissivity (T) and electrical conductivity (EC) values. The BDN parameters: prior probabilities and Conditional Probability Tables - CPTs) have been identified for each of the three zones. Three groups of management scenarios have been developed based on the two decision variables including "Crop pattern" and "Domestic water demand" across the three zones of the study area: 1) status quo management for all three zones represent current conditions; 2) the effect of change in cropping pattern on management endpoints and 3) the effect of future increased domestic water demand on management endpoints. The outcomes arising from implementing each scenario have been predicted by use of the constructed BDN for each of the zones. Results reveal that probability of drawdown in groundwater levels of southern areas is relatively high compared with other zones. Groundwater withdrawal from northern and northwestern areas of the study area should be limited due to the groundwater quality problems associated with shallow groundwater of these two zones. The ability of the Bayesian Decision Network to take into account key uncertainties in natural resources and perform meaningful analysis in cases where there is not a vast amount of information and observed data available – and opportunities for enabling inputs for the analysis based partly on expert elicitation, emphasizes key advantages of this approach for groundwater management and addressing the groundwater related problems in a data-scarce area.

Keywords: Bayesian decision network; Conditional probability tables; Groundwater resources; management scenario; Netica; data scarcity.

Introduction

Groundwater resources management plays a key role in conserving the sustainable resource exploitation in arid and semi-arid areas such as Iran. There are several powerful groundwater quantity and quality management tools including various optimization models and integrated modelling and statistical tools like mathematical programming techniques such as linear programming (LP) (Han et al., 2011; Usul and Balkaya, 1993); nonlinear programming (NLP) (Mantoglou et al., 2004); mixed-integer programming (MIP) (Psilovikos, 1999); optimal control theory-based mathematical programming, differential dynamic programming (DDP) (Culver and Shoemaker, 1993); combinatorial optimization (CO) (Su et al, 2007); stochastic programming (SP) (Li et al., 2009); Numerical groundwater model (Sanford, 2002) and multiple objective programming (Das and Datta, 2001; Yapo et al., 1998; Gorelick, 1983).

Bayesian Decision Network is an approach that is increasingly being used as a probabilistic graphical model in support of natural resources management and environmental modeling as well as it is particularly beneficial for the groundwater management (Martin de Santa Olalla et al., 2007; Fienen and Plant, 2015). Uusitalo (2007) reviewed the advantages and challenges of the application of Bayesian networks in environmental modeling. Results showed that Bayesian networks are useful addition to the toolkit of environmental scientists. Henriksen et al. (2007) applied the Bayesian Network to aquifer management planning in Denmark. The focus was on groundwater quality and on the effects that voluntary farming contracts might have on it. Martin de Santa Olalla et al. (2007) considered the planning of sustainable withdrawal from a large aquifer in Eastern Mancha, Spain to assess the potential of Bayesian networks to water resource management and modelling. Ticehurst et al. (2007) applied Bayesian Network in assessing the sustainability of coastal lake-catchment systems in New South Wales, Australia. The actions they dealt with were different farm management practices and new urban developments. Cain (2001), Bromley et al. (2005) and Pollino and Henderson (2010) provided several comprehensive guidelines on the use of Bayesian networks to support the participatory planning. Farmani et al. (2009) used a Bayesian belief network and evolutionary multi-objective optimization to propose an integrated methodology for incorporating available evidence to assist water managers evaluate implications, including costs and benefits of alternative actions, and present best decision process under uncertainty. Giordano et al. (2013) developed Bayesian Belief Networks to simulate farmers' behavior considering the groundwater management and to evaluate the impacts of protection strategy in order to facilitate the conflict analysis process in a Mediterranean area.

The following section outlines an introduction to Bayesian networks. The next section provides a brief summary description of the study area. The problem to be examined is then explained and the variables and probability tables are presented. These will be followed by providing some groundwater management scenarios. The final section discusses the results and groundwater quality and quantity endpoints.

Bayesian Network

Bayesian Network is a probabilistic and graphical model that represents a set of variables and probabilities related to each one. Bayesian network is a directed graph where nodes are the variables in the management problem (Davies, 2007; Qian and Miltner, 2015). A Bayesian network can be defined as: "a number of nodes representing random variables that are interacting with each other. This interaction is expressed by communication between nodes" (Cain, 2001).

Each BN consists of three major components: a set of nodes (management system variables), a set of arrows (causal relationships between variables), and a set of conditional probabilities. In general, nodes are parent or child. A node will contain a prior probability table if it doesn't have any parents, and it contains a conditional probability table (CPT), if the node has parent(s) (McCann et al., 2006).

Model development process is as follows:

- Construction of model framework

- Classification of nodes

- Quantify the variables and construction of probability tables (Kuikka and Varis, 1997).

When new evidence or data is entered in the Bayesian decision network (BDN) the prior probabilities are updated and a posterior probability distribution is computed in the BDN by use of Bayes' Theorem (Goulding et al., 2012).

Bayesian Decision Networks (BDNs) are defined as Bayesian networks adapted to include Decision (management option) node representing the decision being made at a particular point in time. They are regarded as a useful tool for putting the decision process into graphical form, for holding relationships between variables, and the expected effects of management decisions will be analyzed while considering the associated uncertainties (Catenacci and Giupponi, 2009; Sadoddin et al., 2003; Ames and Neilson, 2001).

Some advantages of this approach over other tools can be summarized as follows:

- Bayesian Networks clearly take into account uncertainties involved in model variables due to incomplete or scarce data and knowledge. Probabilities represent the uncertainties. In other words, the relationships between input variables and their relevant parameters are provided by Bayesian networks as a probabilistic representation rather than exact values (Uusitalo, 2007).

- Variables in natural systems are mostly dependent on cause and effect relationships and quantifying can be difficult due to the lack of proper data or to poor comprehension. Bayesian Decision Networks use various sources of data from diverse disciplines (e.g. social science and natural science, like hydrology and ecology) and integrate them with expert opinion and stakeholders' input (Varis, 1997; Cain, 2001; Martín de Santa Olalla et al., 2007; Barton, 2016).

- The graphical nature and visual easiness is another notable feature of the Bayesian networks. A visual display of the cause effect relationships in the model clearly facilitates active involvement of stakeholders who have diverse backgrounds (Bacon et al., 2002) in the development and validation of Bayesian networks.

To investigate the Bayesian Decision Network's potential, a case study in the field of groundwater management was considered in Kord kooy plain in north of Iran.

This paper focuses on the capability of Bayesian networks to link different types of information and represent uncertainties by using the probabilities instead of exact values. Moreover, this probabilistic framework supports experts' opinion in groundwater management and decision making. The resulting model is applied to 1) estimate the probability of increasing or decreasing trend for groundwater quality parameters within the study area under three management scenarios and 2) estimate the probability of decline and rise in groundwater levels under these scenarios.

As mentioned before, being a decision tool for participatory decision making is one of the advantages of the Bayesian decision network, especially in case of scarce data and conflict of interests. As a result, choosing stakeholders to design the network, is an important issue (Zorrilla et al, 2010). In Kordkooy plain, a lengthy participatory process occured. Three groups of participants with conflict of interest involved in preparing the decision network:

- the "Regional Water Authority of Golestan province" with water management interest considering the water quantity and quality constraints, which depends on Iran's Ministry of Energy and is responsible for water policy;

- "Agricultural Jihad Organization of Golestan province" with agricultural development interest which depends on Iran's Ministry of Agriculture Jihad being responsible for the oversight and implementation of agricultural policies and linked to the farming community and farmers who account for approximately 90% of the total groundwater withdrawals in the Kordkooy region; and

- experts from academia, environmentalists and researchers.

They contributed through several meetings held to discuss water management issues and problem definition in the study area. These meetings allowed participants to serve the purpose of discussing groundwater management issues from a general perspective to agricultural and hydrologic aspects. This participatory process included two parts, in the first part the groundwater management issues were discussed, and the second part was devoted to BDN development process. At all steps of the research, all participants were consulted for their views and were kept informed about each stage or news regarding the research process. Then the states (of each node) and the conditional probabilities (CPTs) were filled by the researchers according to the input from participants.

The general trend of threats and challenges in groundwater resources of the study area are available. Using the BDN in this research provides a more complete understanding of variables and trends affecting the groundwater quality and quantity of study area, and clearly presents the results in terms of probability of each state of variables and makes the decision making process easier.

Case Study Overview and Management Problems

Kord Kooy plain in north-east of Iran and south of the Caspian Sea, has been selected as the study area (Figure 1). This region is at(53°, 52′) to (54°, 21′) E longitude and (36° 41′) to (36° 59′) N latitude. . The southern area is mountainous and the north is mostly flat plains. The study area has a mild and temperate Mediterranean climate. The average annual precipitation in Kord Kooy plain is 590 mm. The area of Kord Kooy plain is about 214 km2. The study area is limited in the north, to the Qara Su River and in the south, to southern mountains of Kord Kooy and in the west and northwest from the Baghu river to the Caspian Sea and in the East to the Shamushak River. It is an alluvial unconfined aquifer. At margin of mountains area, alluvial plain comprising mainly rubble sand and gravel and at the northern parts, the grain size is reduced and leads fine-grained clay layers (Golestan Regional Water Authority, Ministry of Energy, Iran Water Resources Management, 2010). Agriculture can be defined as the major land use in the area. The major portions of abstractions are via dug wells which supply water for agricultural purposes. 90 percent of the total annual water utilization in the study area is used for agriculture, whereas the percentages for domestic and industrial water demands are 9 and 1 percent respectively (Golestan Regional Water Authority, Ministry of Energy, Iran Water Resources Management, 2010).

Major challenges present in groundwater resources management of the study area include:

- High risk of groundwater level depletion at southern areas: In some years, more than 2.5 m drop in groundwater level has occurred, which decreases gradually towards the north and northwest (where there is groundwater discharging area) (Golestan Regional Water Authority).

-Undesirable groundwater quality in north and northwest (Golestan Regional Water Authority): This part of the study area is coastal region where the location of groundwater discharge into the sea is. Therefore, this contributes to the increased occurrences of the Electrical Conductivity values in groundwater (maximum amount of 4000 μmhos/cm) in these areas with high salinity (according to Wilcox diagram).

In order to better implement the groundwater resources management policies, based on the geological characteristics, groundwater quality parameters and groundwater hydrogeological properties , the study area was sub-divided into three zones from north to south (figure 1):

-zone 1, includes the southern and south-eastern and south-western parts of the study area.

-zone 2, includes central parts of the region, from west to east.

-zone 3, includes northern and northwestern parts of the study area (Supply of drinking water to City of Kord Kooy and Torkaman Port, Golestan province Regional Water Co, 2010).

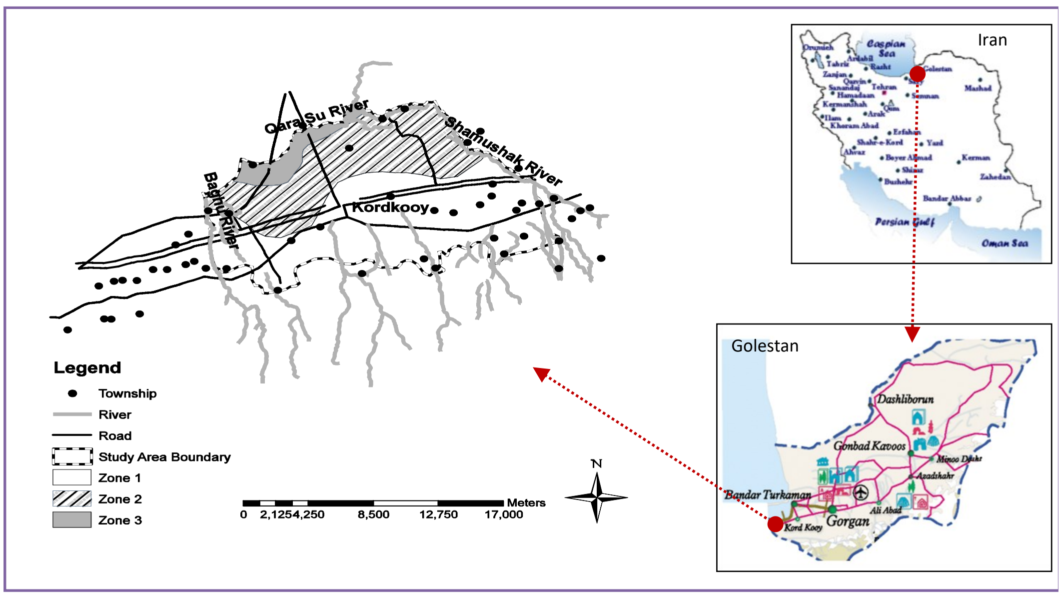


Fig. 1
Location of the study area and segmentation into three zones

Table 1 illustrates the values of electrical conductivity and transmission coefficients and the area of each zone.

Table 1
Characteristics of the three zones

zone	Electrical conductivity (µmhos/cm)	Transmission coefficient (m^2/day)	Area (Hectare)
1	600-1200	550-700	12684
2	1200-2000	400-550	7637
3	2000-4000	200-400	1372

There are a lot of uncertainties regarding current conditions of the study area. There are a large and unknown number of illegal wells scattered within the study area. Data regarding the actual land use situation representing crop production and cultivated land areas are not available and they may be different from published official agricultural statistics. The main reason for this is that the most practiced form of agriculture in the study area is traditional farming and cultivated areas or crops can be varied from year to year. In addition to the lack of accurate input information on agricultural crops, there are sparse measurements of groundwater data (levels and quality), imperfect groundwater level monitoring network as well as some missing data from time series records. Hence, there is uncertainty in conjunction with the real volume of groundwater abstraction which the Bayesian Networks can take into account, due to the tools suitability for dealing with uncertainty in available data and knowledge.

Kord Kooy Groundwater Management Model Development

Problem description

In the first step, the groundwater management problem must be formularized as a BDN Graph, providing an opportunity for stakeholders and decision-makers to create a first-cut assessment of the main variables, decisions, consequences and relationships in the problem (Ames et al., 2005, Goulding et al., 2012).

Figure 2 shows the BDN Graph of Groundwater Management of Kord Kooy Plain (GMKP), including variables and the relationships between them. For groundwater management in the three zones of the study area, two distinct conceptual models were developed. Groundwater management of zones 2 and 3 (GMZ2 & GMZ3) are based on one conceptual model and GMZ1 is based on another exclusive conceptual model. Only in the zone 1, quality of groundwater is suitable to be used for drinking water supply. Total domestic water demand of three zones is supplied from groundwater resources of zone 1. Therefore, BDN of GMZ1 contains the node of "Domestic Water Demand". Table 2 introduces a list of model variables and brief description of them.

Domestic Water Demand (D-WD) and Crop Pattern (C-P) are "Input" and "Decision" nodes. These variables are directly modified by political and management decisions. Intermediate nodes include Agricultural Water Demand (A-WD), Groundwater Withdrawal (G-W) and Groundwater Level Drawdown (GL-D). Based on conceptual model of GMKP BDN, A-WD is affected by Crop Pattern node and G-W is dependent on the amount of Agricultural Water Demand, also Groundwater Withdrawal impact on GL-D. Two endpoints which indicate the groundwater quality criteria are Electrical Conductivity and Chloride. They are directly impacted by the Groundwater Level Drawdown. In which the impact of decision nodes (C-P and D-WD) on the groundwater quality criteria (CL and EC) and groundwater quantitative criteria (GL-D) is investigated.

The variables were discretized into distinct states. Discretization of decision nodes consists of two states “A” and “B” for crop pattern and two states for domestic water demand, and including three distinct states for other variables. Each of groundwater quality end nodes was discretized into four specific states. Selected states for each node are described in more detail in the next sections.

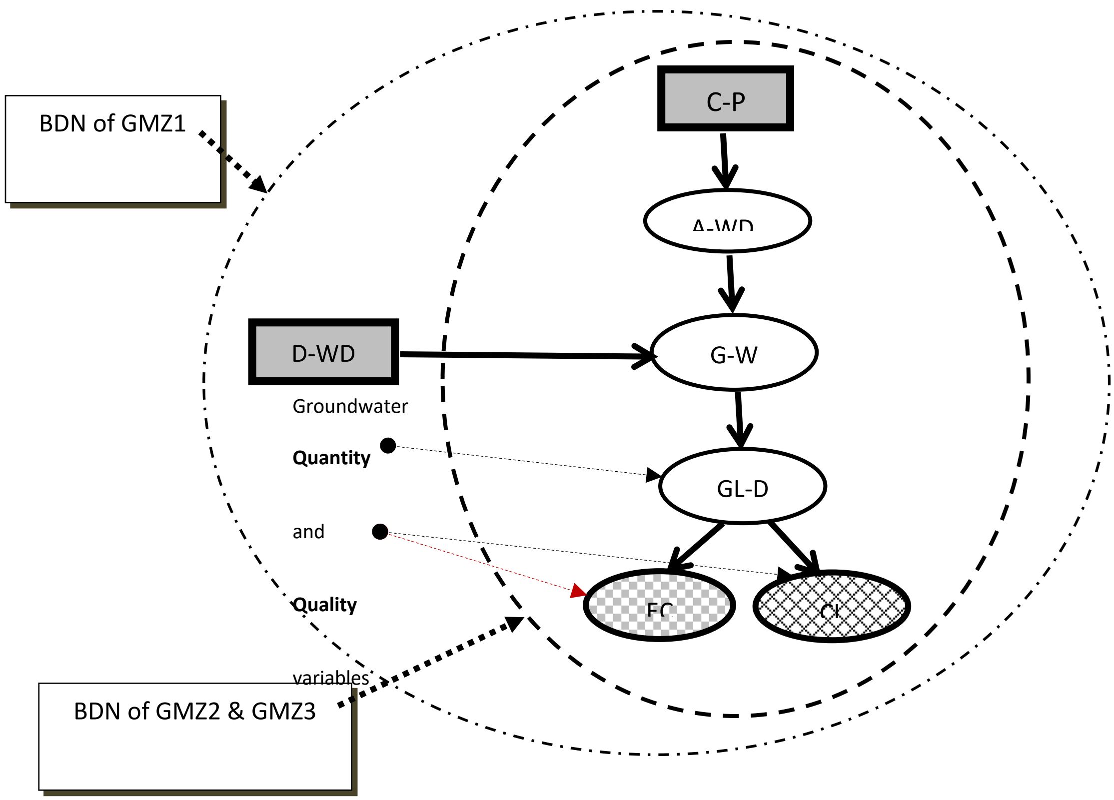


Fig. 2
Kord Kooy Plain BDN Graph for groundwater management

Table 2
BDN variables of Groundwater Management of Kord Kooy Plain (GMKP)

Group	Node Name	Type	Description
Input nodes	C-P	Decision	Cropping Pattern

	D-WD	Decision	Domestic Water Demand
Intermediate nodes	A-WD	State	Agricultural Water Demand
	G-W	State	Groundwater Withdrawal
	GL-F	State	Groundwater Level Fluctuations
End nodes (Output)	EC	State	Amount of Electrical Conductivity in groundwater
	CL	State	Amount of Chloride in groundwater

The targets of the groundwater quantity and quality management of Kord Kooy plain are: 1) reduce the probability (risks) of excessive groundwater level drawdown in zone 1 and groundwater table fluctuations control within the zones 1 and 3, 2) increase the probability of improved groundwater quality in zone 3 and decreasing water quality risk of zones 1 and 2. BN concerned nodes with these management endpoints are shown in Figure 2 as GL-F (Groundwater Level Fluctuations) and EC and CL (as groundwater quality endpoints).

The software used for building the BDN was Netica (Norsys Software, 1992-2011). This software utilizes the Bayes´ theorem for calculating the conditional probability of a variable depending on a previous one by the propagation of the probability. The Netica software generated conditional probability tables (CPTs) based on the type of variables and number of states. The Netica can couple with different programming codes by Application Programming Interface (API), and allow you to build your own Bayesian networks and influence diagrams, do probabilistic inference, learn nets from data, modify nets, and save and restore nets (Norsys Software, 1992-2013; Fienen and Plant, 2015).

Preparation of data and probability tables

Previous BN studies have shown that the information incorporated into these models can be collected from empirical investigation, experimental data, procedure based modelling, and expert judgment, or a combination of all cases (Ames et al. 2005, Bromely et al. 2005). The key to constructing an appropriate BN is to have the best available data with which to populate the probability tables. In some instances the data for a variable are sparse or non-existent. In these cases the conditional probability tables (CPTs), can be constructed by relying on information obtained from experts elicitation and stakeholders knowledge (Ames, 2005; Bromley, 2005; Botsis et al., 2012). In this study several sources of data were considered to establish the probability tables for the GMKP BDN. These include reports on land use and crop patterns, climatic and meteorological data to calculate the agricultural water demand, information regarding domestic water consumption, observation wells and water well operation data, Electrical Conductivity and Chloride concentration observations and using expert knowledge.

Cropping Pattern

Cropping pattern was defined as the parent node of agricultural water demand (A-WD). Annual records of agricultural information between 1998 and 2011 were used to offer two types of cropping pattern and estimate the prior probability of each type. These two proposed cropping patterns are based on the observations during the study period on cultivated crops and the most prevalent cropping patterns which have been implemented in the study area. Table 3 illustrates both proposed cropping patterns and their prior probabilities. Wheat, barley, rice and cotton are major crops in the study area. In cropping pattern A, maximum percentage of area under cultivation were assigned for the crops with higher water demand (rice and cotton) and minimum percentage of the area were specified for those crops that have a lower water demand (Ringler and Zhu, 2015; Mekonnen and Hoekstra, 2010), (wheat and barley). In contrast, in cropping pattern B, maximum proportion of total cultivated area were considered to be under cultivation of crops with lower water use (wheat and barley). Cropping pattern A includes more water requirements compared to B.

Table 3
Two types of cropping pattern (in terms of percentage of total area under cultivation) and prior probabilities (%)

Crop	**State name**		**Growing period**
	A	**B**	**days**
wheat	60%	70%	117
barley	2%	5%	78
rice	25%	15%	169
cotton	13%	10%	188
crop water requirement within the study area (million cubic metres per year)	129.09	106.48	
Prior Probability	64%	36%	

Agricultural Water Demand

The CROPWAT program (version 5.7) developed for the FAO Penman-Monteith method (FAO, 1998) was applied for estimating the crop water requirement of crops considered. Total amount of current agricultural water demand (node A-WD) in the study area was calculated based on existing cropping patterns (A and B) and change in area of agricultural lands in each zone. The range of the calculated values was estimated from 2 MCM (million cubic metres) to 75 MCM per year. The data was broken down into three categories as “AWD_1”, “AWD_2” and “AWD_3”. Due to the differences in the value of agricultural area in each zone, the amount of agricultural water demand are significantly different in each zone relevant to the given cropping patterns, therefore a specific CPT for P(A-DW | C-P) for each zone was computed using these states as shown in Table 4.

Table 4
CPT for P(A-DW | C-P)

		Agricultural Water Demand (A-WD)		
Zone	**Cropping Pattern (C-P)**	AWD_1	AWD_2	AWD_3
1	A	0%	10%	90%
	B	0%	20%	80%
2	A	0%	75%	25%
	B	0%	85%	15%
3	A	85%	15%	0%
	B	90%	10%	0%

Domestic Water Demand

Domestic water demand (D-WD) is a decision node that has no parents and directly affects the groundwater withdrawal variable. It is relevant only with conceptual model of zone 1 as mentioned earlier.

The per capita domestic water consumption was estimated based on reports and expert opinion from a consulting group of Golestan Regional Water Company. The estimated per capita domestic water consumption in the case study is about 200 litres per day (L/d) as an average based on taking both urban (almost 67823 people) and rural (almost 61307 people) areas (Iran, Islamic Rep. - General Census of Population and Housing 2006) into account. Population of the three zones was determined around 12913 people according to the last population and housing census (2007). Therefore the total calculated value for domestic water demand is equal to 9.43 MCM/yr under current conditions of the study area. D-WD variable was categorized as “DWD_1” or “DWD_2” using the threshold value of 10 MCM/yr as a breakpoint to accentuate the status quo and future changes in population of the study area. Prior probabilities table of domestic water demand (Table 5) highlights the future prospects of the study area. It is shown that the population growth in future can increase the domestic water demand and subsequently groundwater withdrawal. Therefore the probability of DWD_2 that is currently zero can be changed in the future.

Table 5
Prior Probability of domestic water demand (D-WD)

State name	Range	Prior Probability
DWD_1	<10 MCM/yr	100%
DWD_2	>10 MCM/yr	0%

Groundwater Withdrawal

According to the proposed BDN graph, groundwater withdrawal variable is the child of both domestic water demand and agricultural water demand in zone 1, and "G-W" is only the child of agricultural water demand in zone 2 and 3. These relations involve estimates of two CPTs, P(G-W|A-WD) for zone 2 and 3 and P(G-W|A-WD, D-WD) for zone 1. Groundwater withdrawal data (including the annual discharge of each well, geographic coordinates of the wells, well drilling start date and well name) were collected from both drinking water wells and irrigation water wells located in study area from 1980 to 2011 (Golestan Regional Water Authority). Water well location maps were prepared separately for each zone in GIS by using field data. Annual groundwater withdrawal values (MCM) were estimated separately for each zone. The calculated groundwater withdrawal values for zones are 21 to 31 MCM/yr, 12 to 21 MCM/yr and 0.7 to 1.4 MCM/yr orderly. These data were divided into three subfields as "G-W_1", "G-W_2" and "G-W_3" using the 15 MCM/yr and 25 MCM/yr as two breakpoints so that joint ranges of observations occur in each category in order to avoid getting very few data in any state. The challenge in deriving probabilistic relationships between above variables is lack of measured data and the corresponding CPTs were constructed by using proper limits according to expert opinion, including information from the scientific literature. The expert opinion that supported the formation of these CPTs was based on observations of the effect of D-WD and A-WD in groundwater withdrawal. The Golestan Regional Water Company was consulted to estimate P(G-W|A-WD) related to zone 2 and 3 (see Table 6) and P(G-W|A-WD, D-WD) related to zone 1 (as shown in Table 7).

Table 6

CPT for P(G-W|A-WD)

Agricultural Water Demand (A-WD)	Groundwater Withdrawal (G-W)		
	G-W_1	G-W_2	G-W_3
A-WD_1	95%	5%	0%
A-WD_2	5%	40%	55%
A-WD_3	0%	10%	90%

Table 7
CPT for P(G-W|A-WD, D-WD)

Agricultural Water Demand (A-WD)	Domestic Water Demand (D-WD)	Groundwater Withdrawal (G-W)		
		G-W_1	G-W_2	G-W_3
A-WD_1	D-WD_1	90%	10%	0%
A-WD_1	D-WD_2	80%	20%	0%
A-WD_2	D-WD_1	0%	25%	75%
A-WD_2	D-WD_2	0%	15%	85%
A-WD_3	D-WD_1	0%	10%	90%
A-WD_3	D-WD_2	0%	5%	95%

Groundwater Level Fluctuation

Groundwater level fluctuation is dependent on the groundwater withdrawal variable. Monthly average of groundwater level measurements were collected from 21 observation wells at the study area for 19 years in the period from 1992 to 2011. These observation wells are distributed among the study area to illustrate the trend and fluctuations of groundwater level all over the Kord Kooy plain. The data were used to derive a CPT for P(GL-F|G-W). The important sources of recharge are underground flows from mountain into the plain and recharge from agricultural irrigation. In this study, the annual groundwater level fluctuations are investigated mainly in response to the changes of groundwater withdrawal quantities. Main portions of discharge are artificially through a number of dug wells. The unit hydrograph is drawn based on the information obtained from 21 observation wells exclusively for each zone over the period of October 1992/1993 to October 2010/2011 and provides a way of comparing ground water levels year to year in each zone of the study area (Figure 3).The hydrograph shows annual fluctuations characterized by a gradual rise in head from October to April/May and a rapid drop from May/June to October. The hydrograph shows that in general, there is a decline in the water level in zone 1 in the range of 0.05-2.4 m and there is a rise in water level in zones 2 and 3 in the range of 0.1-1 m and 0.2-0.8 m respectively. These data were categorized as “GL_D1”, “GL_D2” and “GL_R” while D and R indicate the Drawdown and Rise in groundwater level respectively. A CPT for P(GL-F|G-W) was concluded using these states and is shown in Table 8. The resulting CPT accentuates the concept that the highest value of drawdown in groundwater level occurs in state of G-W_3 (maximum groundwater withdrawal) and maximum rise happen in G-W_1 (the lowest groundwater withdrawal)

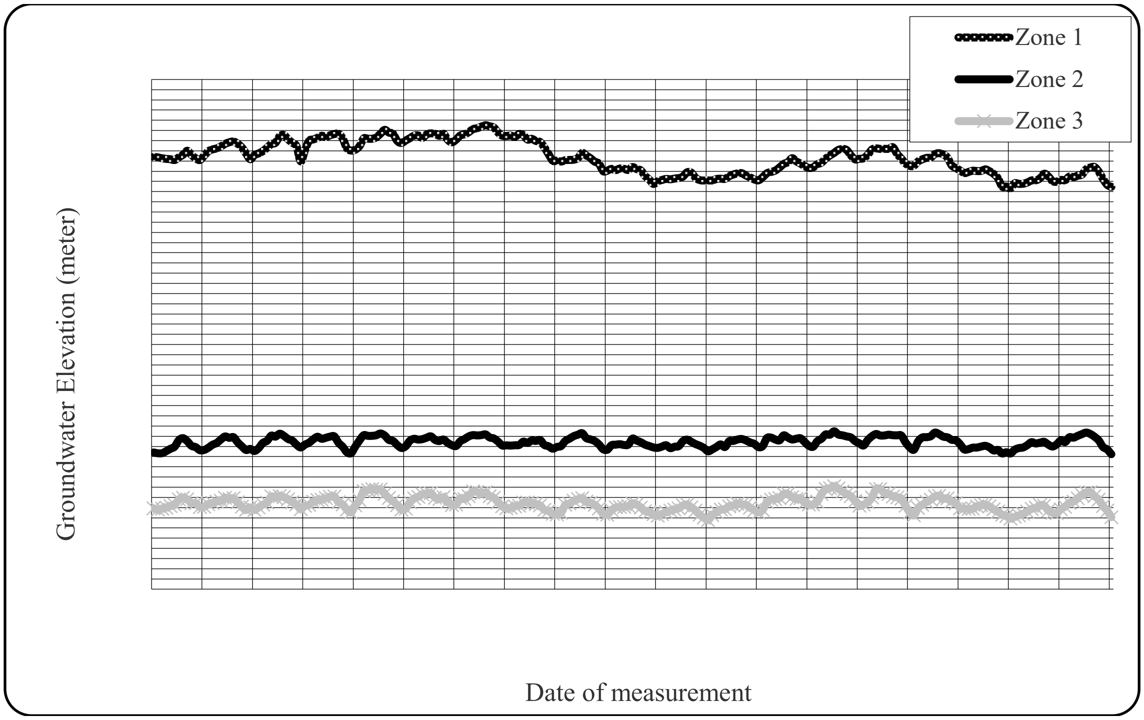


Fig. 3

The Groundwater Unit Hydrograph in three zones of the study area

Table 8

CPT for P(GL-F|G-W)

	Groundwater Level Fluctuation		
Groundwater Withdrawal	GL_D1 1-2.5 m	GL_D2 0-1 m	GL_R 0-1.5 m
G-W_1	0%	25%	75%
G-W_2	0%	30%	70%
G-W_3	29%	14%	57%

Groundwater Qualitative Variables

Groundwater qualitative variables, EC and CL can be described as only dependent on groundwater level fluctuation (GL-F). These relationships necessitate characterization of two CPTs, P(EC|GL-F) and P(CL|GL-F). This study deals with CL and EC as two common selected groundwater quality parameters important in drinking water and agricultural water in the aquifer of Kord Kooy plain. The most efficient water quality guideline on crop productivity is the water salinity hazard (Rhoades et al., 1992). For reasons of analytical convenience, a practical index of salinity is electrical conductivity (EC). Chloride (Cl) is a negative ion in groundwater and human activities can contribute to the presence of chloride in well water (such as sewage contamination and leachate from dumps or landfills). Groundwater quality data was determined by taking samples from 10 of the wells within the study area for 10 years in the period from Nov 2001 to Nov 2011. Interpolation techniques of ArcGIS 9.3 and ArcGIS Spatial Analyst were used to obtain the spatial distribution of groundwater quality parameters. These data produced maps showing concentrations of chloride and electrical conductivity during the period. Based on the generated maps, the average quality parameters were estimated for each zone annually. The data ranges are shown in Table 9. Groundwater electrical conductivity (EC) and chloride ion concentration values were classified considering the Wilcox diagram and Schuler diagram (Meftah and Hezarjaribi, 2011) respectively. Two CPTs for P(EC|GL-F) and P(CL|GL-F) were computed using defined states and are shown in Tables 10 and 11.

Table 9
Data ranges of CL and EC

	CL (mg/l)	**EC (µmhos/cm)**

Zone 1	118-420	900-1500
Zone 2	190-625	1400-2000
Zone 3	240-1020	1650-2900

Table 10
CPT for P(EC|GL-F)

Groundwater Level Fluctuation	**Electrical Conductivity (µmhos/cm)**			
	EC_1 100-250	EC_2 250-750	EC_3 750-2250	EC_4 >2250
GL_D1	0%	0%	100%	0%
GL_D2	0%	0%	88%	12%
GL_R	0%	0%	80%	20%

Table 11
CPT for P(CL|GL-F)

Groundwater Level Fluctuation	**Chloride (mg/l)**			
	CL_1 <175	CL_2 175-350	CL_3 350-700	CL_4 700-1400
GL_D1	50%	50%	0%	0%
GL_D2	19%	44%	25%	12S%

GL_R	13%	34%	33%	20%

The completed BDN, considering the water management interest through "domestic water demand" as a decision node and agricultural viewpoint by "cropping pattern" as another decision node, was presented to experts for evaluation, and all involved teams agreed on components of the model. As previously described, cropping pattern and domestic water demand have been defined as decision nodes in the BDN, hence the management scenarios were developed to consider the effect of changes in the different states of these decision nodes on the management endpoints. As a result, three groups of scenarios (status quo, change in cropping patterns, and later increased domestic water demand in the study area) were developed for testing the behavior of the entire BDN, with specific focus on the prediction of changes in management endpoints groundwater quantity and quality. After applying management scenarios, the status quo scenario results (demonstrating the current conditions of the study area) were compared to the results of the other two scenarios as described in the next section.

Scenario Planning For Groundwater Management

Scenario planning provides investigation of a variety of plausible alternative futures by taking into account the possible interactions across a variety of motive forces and highlights the risks and opportunities associated with each. Three groups of potentially acceptable scenarios that can be implemented for groundwater management in the aquifer of Kord Kooy plain were planned to discuss management endpoints responses to such scenarios:

1) status quo management for all three zones represents current conditions (the conditions in which CPTs were derived)

2) the effect of change in cropping pattern as a decision node on management endpoints (use exclusively one of the cropping patterns A or B for each zone)

3) the effect of increasing domestic water demand as a decision node on management endpoints in the future (exclusively for zone 1)

Management scenarios are shown in Table 12.

Table 12
Management scenarios

Group	**Name of scenario**	**Description**
1	SQ-Z1	status quo management in zone 1
	SQ-Z2	status quo management in zone 2
	SQ-Z3	status quo management in zone 3
2	A-Z1	exclusively using cropping pattern A in zone 1
	A-Z2	exclusively using cropping pattern A in zone 2
	A-Z3	exclusively using cropping pattern A in zone 3
	B-Z1	exclusively using cropping pattern B in zone 1
	B-Z2	exclusively using cropping pattern B in zone 2

	B-Z3	exclusively using cropping pattern B in zone 3
3	DW-A	increasing domestic water demand and exclusively using cropping pattern A
	DW-B	increasing domestic water demand and exclusively using cropping pattern B
	DW-SQ	increasing domestic water demand and using cropping pattern under status quo

Results

The resulting probability distributions of selected combinations of management scenarios were calculated by the Netica software and compared to achieve an ultimate management view. This developed model was able to handle several different types of variables at the same time (discrete for cropping pattern and continues for other variables) and all the different variable types fell in the same single framework.

Figure 4 illustrates the BDN (for zone 1) with total probabilities of states of all nodes under status quo management scenario (as reference scenario) in the Netica software. Probabilistic results of status quo scenario confirmed the current conditions of qualitative and quantitative groundwater variables in three zones of the study area.

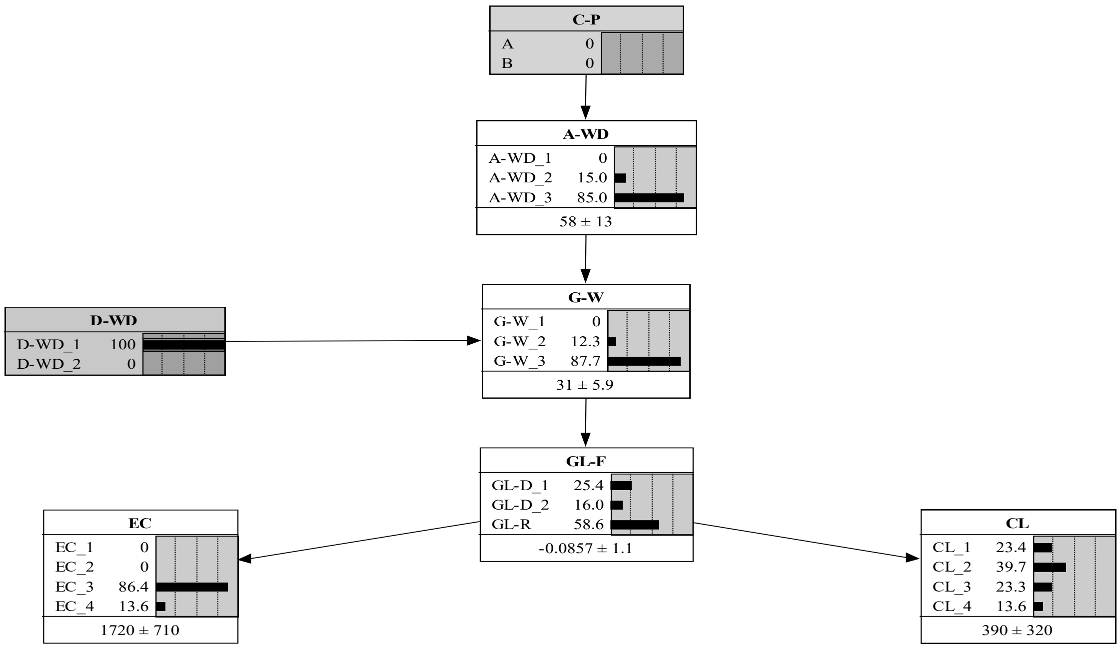


Fig. 4
Full Kord Kooy Groundwater Management BDN for zone 1 with the results under status quo scenario

Status que Scenarios

Figure 5 shows that based upon the status quo scenario, state of GL_D1 (maximum amount of drawdown) to groundwater level fluctuation node (GL-F) is most likely in zone 1 (25.4%). This is due to higher values of groundwater withdrawal from wells in zone 1. Moving towards zones 2 and 3 and ultimately to the sea, lower values of groundwater withdrawal from wells will cause the groundwater level to rise gradually. So it is observed that state of GL_R to GL-F node has the highest probability in zone 3 (73.3%).

Based upon the current knowledge of the study area, status quo management scenarios (Fig. 5) result in an expected probability of 0% for states of EC_1 and EC_2 (low and medium classes in the Wilcox classification) and it is most likely to fall between 750-2250 µmhos/cm (EC_3) for each zone (80%). Groundwater resources of zone 3 have the higher probability of EC_4 (EC values above 2,250 µmhos/cm) compared with other two zones. Based on the results obtained from status quo management scenarios, groundwater resources of zone 1 have the lowest amount of EC compared with zones of 2 and 3.

In the case of status quo management scenarios, there is more than a 35% possibility that chloride content of groundwater resources in each zone of study area fall in the CL_2 class (acceptable values of chloride for drinking water within the range 175-350 mg/l). Groundwater resources of zone 1 have the highest probability of CL_1 (chloride values below 175 mg/l) and states of CL_3 and CL_4 (middle and inappropriate levels of chloride for drinking water between 350-700 and 700-1400 mg/l) have the higher probability in zone 3 compared with other zones.

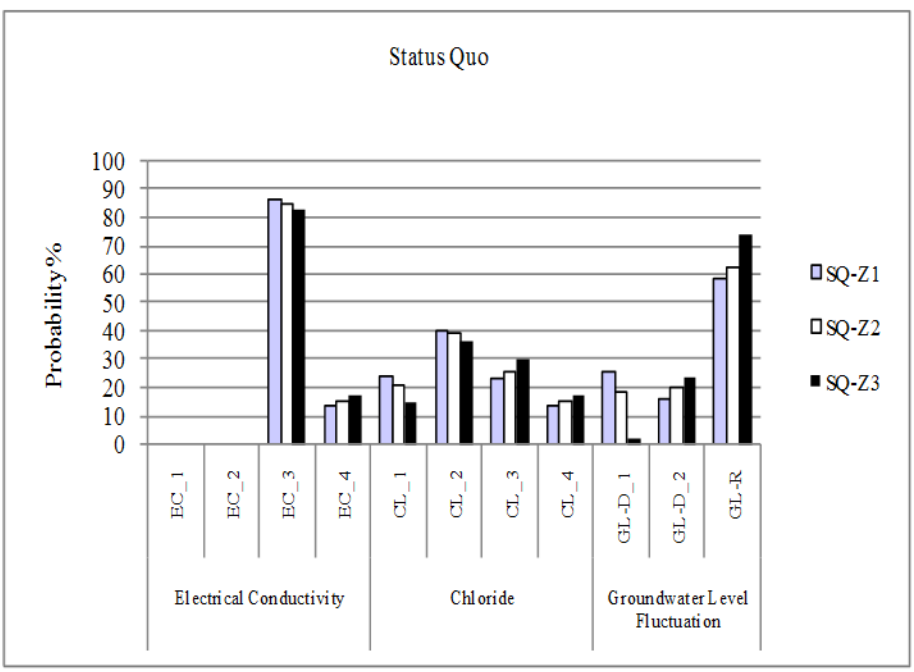
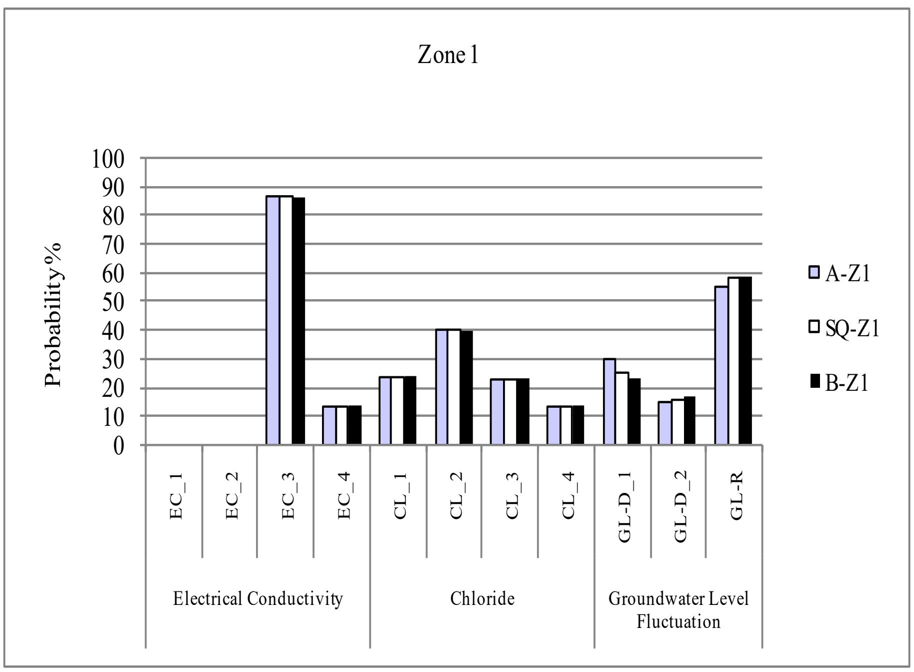


Fig. 5
Total probabilities of states of all management endpoints for each zone under status quo management scenarios

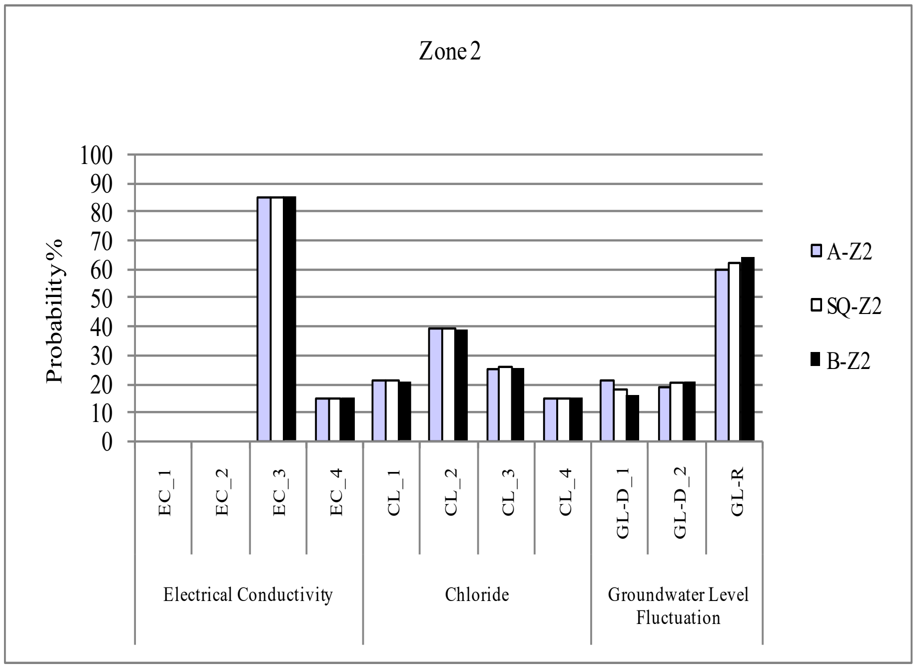
Future scenarios

Figure 6 depicts the results under the scenarios of group 2. Accordingly, by entering findings into the BDN for Cropping Pattern node (probability of each cropping pattern A and B is considered to be 100% respectively to evaluate possible effects on other variables expressed by probabilities), probabilities of all states of GL-F node in each zone would be different from related probabilities under status quo scenario A finding of “A” and “B” (cropping pattern) is entered into the BDN model and its impact on states of GL-F variable can be visually represented by probability values (as percentage). Probabilistic representation of results displays that using the cropping pattern A compared with B increases the probability of GL-D1 within the study area (each zone) relative to the status quo and there is higher severity in zone 1, so groundwater resources of zone 1 has the higher probability of drawdown by using cropping pattern A compared to the current conditions. On the other hand, there is a lower probability of drawdown (GL-D1) in zone 1 by using the cropping pattern B compared to status quo. This was largely due to the occurring significant increase in agricultural water demand (A-WD) and subsequently increase in groundwater withdrawal (G-W) and eventually there will be higher probability of GL-D1 by using the cropping pattern A compared with B. Updating existing model is easy, this is one of the most important advantages of Bayesian Networks. Resulting model can be used for computing the probabilities of outcomes of another proposed cropping pattern under varying water supply conditions in study area and stakeholders' priorities in future.

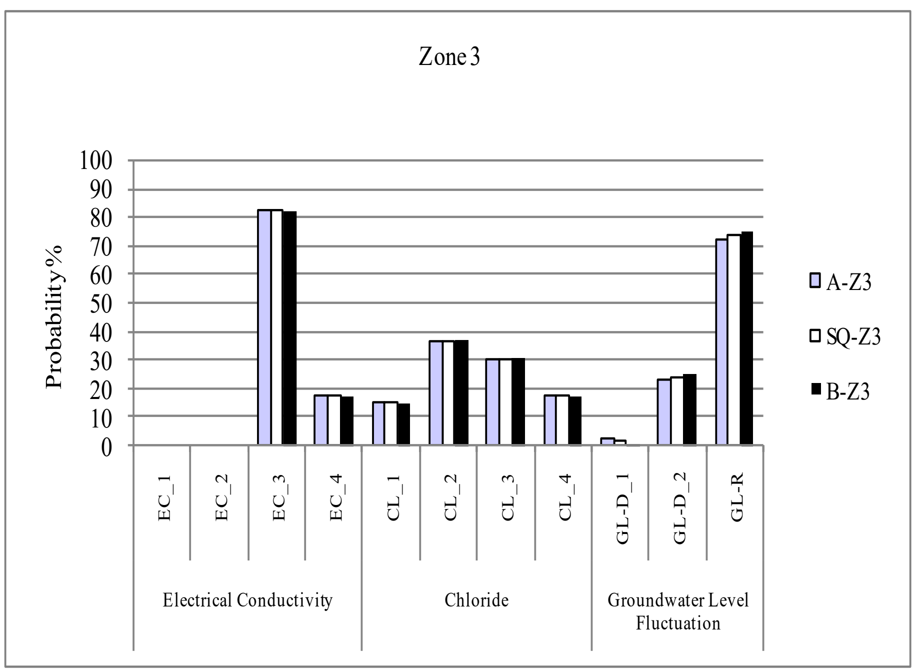
Figure 7 shows the difference in the probability of all states of GL-F node in zone 1 under the scenarios of group 3 which will be expected if the population increases in the future. Overall Fig. 7 (findings at the nodes of D-WD and C-P) indicates that it is more likely that state of GL-D1 will occur in GL-F node compared to prior BDN model of zone 1 (status quo).This highlights that increase in the study area's population makes a push for a greater degree of domestic water demand and therefore higher probability of groundwater level drawdown in zone 1. In the combination of findings at D-WD (state of DWD_2) and C-P (state of A) GL-F node has the highest probability of GL-D1 caused by considering the increased water demand (domestic and agricultural) and consequently impact on the increase in groundwater withdrawal that would significantly increase the groundwater level drawdown in zone 1.



(a)



(b)



(c)

Fig. 6

Probabilities of states of all management endpoints for each zone under management scenarios of group 2 resulting from various findings at the C-P node

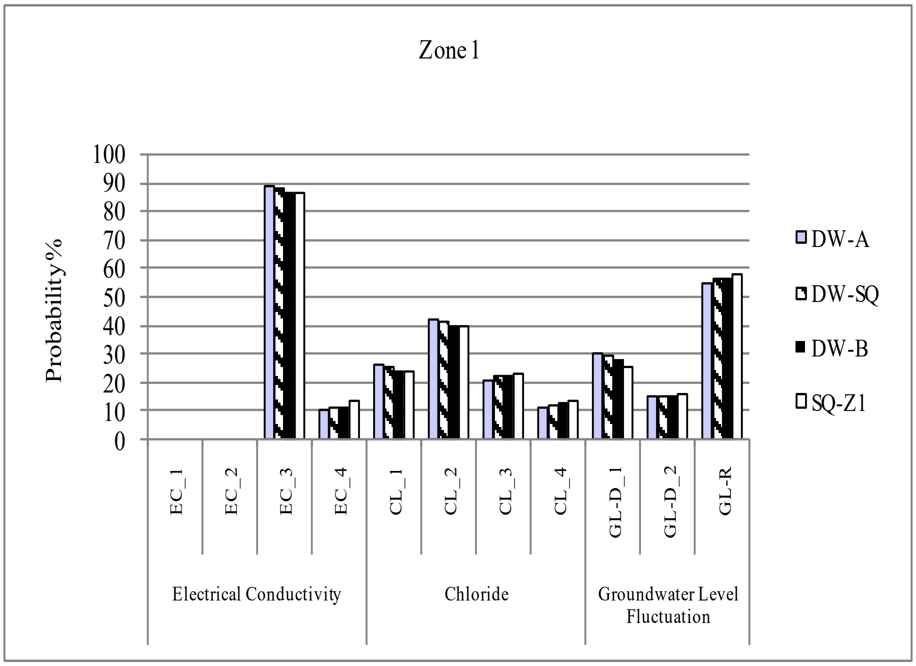


Fig.7

Probabilities of states of all management endpoints for zone 1 under management scenarios of group 3 resulting from findings at the D-WD node

Groundwater Quality Endpoints

Overall, from the groundwater quality point of view, the probabilistic results of status quo management scenarios show that there is a higher probability of being in a suitable position of groundwater quality status in terms of EC and CL in zone 1 compared with other zones. Advancing toward the northern and coastal areas (zones 2 and 3), likelihood of poor groundwater quality (in terms of EC and CL) would increase under current conditions. This is mainly due to location of groundwater resources of zone 1 in highlands of southern Kord Kooy (ground water recharge area) so deposits, are generally coarser-grained alluvial (such as sand or gravel) and the groundwater quality is more suitable whereas advancing toward the zone 2 and zone 3 (northern and coastal areas), deposits are more fine-grained (such as silt, clay, and shale) and there is a risk of saltwater intrusion and evaporates in coastal plain which may lead to increased salinity levels of groundwater. Thus, groundwater quality generally deteriorates from south to north of study area towards the coast.

As noted previously, the second group of scenarios comprises a finding of A and B (types of cropping pattern) entering into the BDN model. Results, presented in Fig. 6, indicate the insignificance of the difference between the probabilities concerning the EC and CL nodes and existing conditions of groundwater quality endpoints. In other words, prior probabilities of states of groundwater quality end nodes (EC and CL) in the study area (all three zones) remain unchanged based on this new evidence entered into the BDN (in the cases of current cropping patterns providing in this study). It is clear that different effects on the current status of groundwater quality endpoints might occur through using another cropping pattern different from present cases.

The behaviour of the BDN model under the third group of scenarios in zone 1 (given in Fig. 7) shows that the likelihood of decrease in chloride and electrical conductivity levels slightly increases by a finding of 100% probability that the domestic water demand (D-WD) node will be in DWD_2 (>10 MCM/yr) state. As previously referred, for the domestic water demand variable, there are two approaches. The first is current domestic water demand pattern and the second is the higher domestic water demand in the future. Therefore, according to the results, the increase in domestic water demand along with population growth in future and subsequently increase in groundwater withdrawal and groundwater level drawdown associated with them will lead at least to slight improvement in groundwater quality endpoints of zone 1 compared to the status quo. There can be two possible reasons for this:

(1) discharges of domestic and industrial effluent to groundwater via absorption trenches or disposal into absorption wells in the zone 1, when the depth to water level is low (in the case of lower groundwater level drawdown), this could lead to a higher likelihood of increase in the values of electrical conductivity and chloride in shallow water table.

(2) it is possible that in zone 1 besides the groundwater resources available in the area of water level fluctuation, there exists a deeper recharge area beneath the zone of fluctuation which still remains unexplored and potentially has fresh groundwater. It is nourished from mountain highlands of south of Kord Kooy (as entry point of groundwater) and then moves into deep layers. It is naturally pushed upward to recharge the aquifer at deeper water level. So, increase in the domestic water demand in the future and higher amount of groundwater withdrawal and higher groundwater level drawdown would cause higher probability of decrease in the values of electrical conductivity and chloride occurring in deeper water level.

Although there is not much difference in groundwater quality endpoints probabilities between third group of scenarios and status quo, however, in the management context, it is important to consider the insignificant change in probable improvement in groundwater quality within zone 1.

Discussion

BDNs are able to take into account key uncertainties in natural resources and explicitly represent those uncertainties due to the use of probability distributions (Uusitalo, 2007). Bayesian Decision Networks give a number of advantages over other decision tools such as:

- Performing a meaningful analysis in cases where there is not vast amount of information and observed data available -even based partly on expert opinion-;
- providing stakeholders' engagement having conflicts of interest and contributing to structuring the participatory process (Bacon et al., 2002);
- inclusion of both qualitative and quantitative knowledge;
- facilitating effective discussions with non-expert stakeholders through graphical interface provided by Bayesian network as a strong tool for visualizing complexity; and
- the ability to carry out rapid updates and simulations in groundwater resources management process (Zorrilla et al., 2010).

In this research, three groups of experts (Regional Water Authority of Golestan province with water management interest; Agricultural Jihad Organization of Golestan province with agricultural development interest; and researchers) contributed to development of the Bayesian decision network through several meetings (in every step of the performing the methodology) in which groundwater management issues of Kord Kooy region was discussed. There are groundwater quality problems in north and northwest of the region, and un-moderated groundwater extraction via a large unknown number of illegal wells is responsible for groundwater level depletion at southern areas. There were conflict of interest between farmers and agriculture sector, water authorities, and environmentalists. Lack of data available especially on deriving the probability tables (for example, CPT for groundwater withdrawal and related nodes) was another challenge in groundwater management of the area.

Under these circumstances BDNs were considered to be a well-suited decision tool to underpin groundwater management in the Kord Kooy plain and other tools were eliminated from the outset.

The results of applied approach were presented to expert participants. There was consensus among participants about the usefulness of the tool especially in similar cases where there is a lack of data which is able to incorporate the stakeholder opinions and values into the decision making. They confirmed that the proposed method allowed the joint evaluation of groundwater quality and quantity management options. Similar outcomes were also depicted by Cain et al. (2003), and Henriksen et al. (2007).

Dividing the study area into three zones based on the hydrogeological properties from north to south helped in better implementation of the groundwater management in Kord Kooy plain. They perceived this as an effective way to consider the hydrogeological limits and differences with in the Kord Kooy region.

The application of the proposed methodology as a practical tool can also be useful for water resources companies and other responsible authorities in groundwater management section. This enables the decision makers to make the most appropriate decisions based on the real conditions of the variables in different zones. It is clear that prioritization of management options to represent the decision maker's preferences and major groundwater problems can help managers to consider various groundwater quantity and quality policy options. This will result in different conceptual models, BDN structure and different management endpoints. In other words, others might have different priorities and collect additional data and information and use it to develop different BDN framework and improve the CPTs relevant to the model.

Thus, further developments in relation to the Bayesian decision network (BDN) to evaluate the impacts associated with a variety of groundwater quantitative and qualitative management policies would improve the managers understanding about different effects and help in making the best choices relevant to the problem at hand.

Conclusions

Groundwater resources management plays a key role in maintaining the sustainable conditions in arid and semi-arid regions such as Iran. Bayesian Decision Network (BDN) methodology was applied for the aquifer of Kord kooy plain in northern Iran. Three separate BDN models were developed for three zones of the study area. To evaluate the possible impacts of future domestic water demand along with population growth and changing cropping patterns on the groundwater resources system of the study area, 12 scenarios were developed and simulated by the models. The results were presented in terms of probability values for groundwater quantity and quality endpoints under deferent management scenarios. Overall, the results revealed that there is a higher probability of drawdown in groundwater levels in zone 1 compared to zones 2 and 3. Groundwater resources of zone 1 are already at risk. So, if the groundwater is over-exploited, it will result in a widespread decline in groundwater level and the aquifer will be unable to meet the demand in the future. Groundwater withdrawal from zones 2 and 3 should be limited due to the groundwater quality problems associated with shallow groundwater in these two zones.

Bayesian decision networks were perceived by experts participating from agriculture sector and water authorities, as effective means to communicate complex issues through a graphical interface, as well as to represent the uncertainty by using the probabilities which implies that the use of Bayesian decision networks in Kord kooy region achieved the goal.

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