Using Bayesian networks to model watershed management decisions: an East Canyon Creek case study

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ABSTRACT

An approach to developing and using Bayesian networks to model watershed management decisions is presented with a case study application to phosphorus management in the East Canyon watershed in Northern Utah, USA. The Bayesian network analysis includes a graphical model of the key variables in the system and conditional and marginal probability distributions derived from a variety of data and information sources. The resulting model is used to 1) estimate the probability of meeting legal water quality requirements for phosphorus in East Canyon Creek under several management scenarios and 2) estimate the probability of increased recreational use of East Canyon Reservoir and subsequent revenue under these scenarios.

Key words | Bayesian networks, water quality modeling, watershed decision support

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INTRODUCTION

Bayesian networks

A Bayesian network (BN) is a directed acyclic graph that graphically shows the causal structure of variables in a problem, and uses conditional probability distributions to define relationships between variables (see Pearl 1988, 1999; Jensen 1996) A simple 3-node BN is shown in Figure 1 including the variables A, B and C. The graph structure indicates that A and B are conditionally independent and that C is conditionally dependent on both A and B. To transform this graph into a BN, the marginal probability distributions $P(A)$ and $P(B)$ as well as the conditional probability distribution $P(C|A,B)$ (read as "the probability of C given A and B") need to be estimated.

To simplify estimating and using these quantities in the BN, the variables are discretized into distinct states allowing one to characterize the continuous probability distributions through a discretized conditional probability table (CPT). Discretization of variables is not a requirement of BNs in general (see Pearl 1988) but is a convention used here to ease computation, elicitation of probabilities from experts and communication of results to stakeholders. The disadvantage of discretization is in the potential loss of information; however, it can be particularly useful in the case of variables with a distinct breakpoint significant to management.

For example, if A and B are each discretized into two states, then the BN model would require estimates of the marginal probabilities $P(A=a1)$, $P(A=a2)$, $P(B=b1)$ and $P(B=b2)$. To complete the BN, and assuming two states for C, then the CPT representing the following conditional probabilities would also be required:

$$P(C=c1|A=a1,B=b1) \quad P(C=c2|A=a1,B=b1)$$

$$P(C=c1|A=a1,B=b2) \quad P(C=c2|A=a1,B=b2)$$

$$P(C=c1|A=a2,B=b1) \quad P(C=c2|A=a2,B=b1)$$

$$P(C=c1|A=a2,B=b2) \quad P(C=c2|A=a2,B=b2).$$

Once these probabilities are estimated, then the BN is complete and propagation of information through the BN can be used to view how decisions and observed conditions

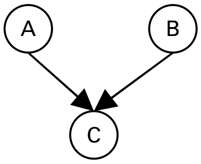

Figure 1 | Simple 3-node BN showing conditional dependence of *C* on *A* and B. *A* and *B* are conditionally independent.

(called "evidence") at one node affect the probable conditions at other nodes. Downward propagation of evidence through the BN is based on the law of total probability:

$$P(c1) = P(c1|a1, b1) \cdot P(a1, b1) + P(c1|a1, b2) \cdot P(a1, b2) + P(c1|a2, b1) \cdot P(a2, b1) + P(c1|a2, b2) \cdot P(a2, b2).$$

Upward propagation of evidence through the BN is based on Bayes' Rule:

$$P(a1, b1|c1) = P(c1|a1, b1) \cdot P(a1, b1)/P(c1).$$

Since their inception, BNs have been used extensively in medicine and computer science (Heckerman 1997). In recent years, BNs have been applied in environmental management studies, including the Neuse Estuary Bayesian ecological response network (Borsuk & Reckhow 2000), Baltic salmon management (Varis & Kuikka 1997), climate change impacts on Finnish watersheds (Kuikka & Varis 1997), the Interior Columbia Basin Ecosystem Management Project (Lee & Bradshaw 1998) and waterbody eutrophication (Haas 1998). As collectively illustrated in these studies, a BN graph structures a problem such that it is visually interpretable by stakeholders and decision-makers while serving as an efficient means for evaluating the probable outcomes of management decisions on selected variables.

Constructing Bayesian networks for watershed management

A generalized approach for developing BNs specifically for watershed management problems is proposed, followed by a case study implementation of the approach. Key elements of the approach are shown in Figure 2 and are described in greater detail as follows.

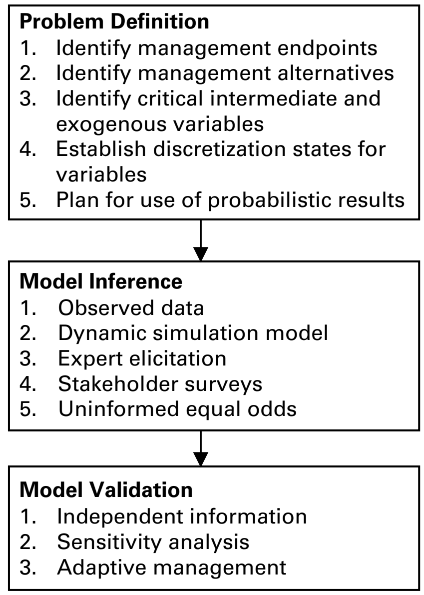

Figure 2 | Generalized approach to developing a BDN for watershed management decision problems.

Problem definition

The watershed management problem must be formulated as a BN graph, providing an opportunity for stakeholders and decision-makers to produce a first-cut assessment of the important variables, decisions, outcomes and relationships in the problem. Variables in a BN are represented by nodes in the graph. The three types of BN graph nodes include: decision nodes (representing sets of distinct management alternatives), utility nodes (representing costs and other value measures) and state nodes (representing variables that can exist in any of several separate states with a certain probability). The BN graph serves as a reference for later data analysis and information gathering used to refine the graph structure and infer probability distributions. The following steps are proposed for building the BN graph.

Identify management endpoints. Selection of endpoints at the outset helps keep the BN focused only on variables significant to the decision problem under investigation. If this is done with the direct input of stakeholders, it has the effect of bringing different interests together to agree on a set of endpoints for evaluation. Additionally, geographic locations (control points) at which the endpoints will be evaluated must also be selected.

Identify management alternatives. Decision alternatives may include, but are not limited to, long-term planning options as well as day-to-day management activities. A separate decision node is added to the BN graph for each set of mutually exclusive alternatives.

Identify critical intermediate and exogenous variables. A minimum number of intermediate state nodes should be selected to define the relationship between management options and endpoints while capturing all variables that decision-makers and stakeholders consider important. In a group setting, this process can iterate until all parties involved agree on a single BN graph structure. Exogenous variables that drive the system, but are not managed (e.g. precipitation), are also identified at this stage.

Establish discretization states for variables. Terciles or quartiles of the data can be convenient discretization states when all that is needed is a distinction between “high”, “medium” and “low.” Alternatively, it may be more meaningful to stakeholders and decision-makers if the discretization is based on values critical to the management problem. For example, a stream segment might have a cold water fishery beneficial use criterion of 22°C and a salmonid spawning beneficial use criterion of 15°C, making these useful breakpoints for three states of temperature. Likewise, a low 7-day average streamflow with a 10-year return period (7Q10) can be a meaningful breakpoint for streamflow.

Identify data sources. It is important to identify data sources at the outset to ensure that all available and relevant information is used in the BN model. This activity may help one to refine the BN model by eliminating graph nodes where no information is available and adding nodes where information is available. This activity will also help identify data gaps where expert judgment may be needed to characterize the relationship between variables.

Plan for use of probabilistic results. For some environmental problems, results may be required or expected to be “true” or “false” (e.g. “the lake is impaired”). However, by definition, results from a BN analysis are probabilistic (e.g. “there is a high probability that the lake is impaired”). Because of this, it is important to establish early on how probabilistic results will be used to address the problem. For example, the plan may be to convert probabilistic results into binary results using some threshold (e.g. if the probability of impairment is over 70% then the lake is reported as impaired). It is also useful to report results in terms of risk (e.g. “under management scenario one, there is a 20% chance that the temperature requirement for salmonid spawning will be exceeded”). Presenting results in this way shifts the burden of assessing risk acceptability from technical analysts to regulators and policy personnel.

Model inference

CPTs that define the probabilistic relationship between variables in the BN can be inferred from a variety of information sources, including observed data, model simulation results and expert judgment. Additionally, economic analyses, stakeholder surveys or expert judgment can be used to estimate cost–benefit utility functions and CPTs where hard data is not available.

Observed data. Observed data can include water quality or streamflow monitoring data, ecological measures, sediment loads, riparian vegetation, recreational use records and other relevant information. Cheng *et al.* (1997) present an algorithm for inferring both the BN graph structure and CPTs from observed data. When the BN graph structure is known, the following steps can be used to infer CPTs from data:

(1) Simultaneous observations of each variable are tabulated and sorted by parent variable.
(2) Observations are converted into categories (*High*, *Medium*, *Low* or *True*, *False*, etc) based on the node discretization defined previously.
(3) For every combination of states of the parent nodes, the number of occurrences of states of the child is counted.
(4) Probabilities are calculated as the number of occurrences of a child state divided by the total number of observations for that combination of parent states.

Dynamic simulation model. A dynamic simulation model can also be used to estimate BN CPTs (for example, see Borsuk & Reckhow 2000). This is particularly useful in cases where there is little or no observed data available to characterize a particular relationship in the BN. In this way, model results are integrated in a single BN with data and expert judgment used to characterize other relationships. The following steps are used to estimate a CPT using a dynamic simulation model.

(1) Construct and calibrate the simulation model.
(2) Identify model input variables corresponding to parent nodes in the BN and model output variables corresponding to child nodes in the BN.
(3) Run the model using an uncertainty analysis technique such as Monte Carlo simulation, varying the selected input variables and calibration parameters about an appropriate distribution.
(4) Tabulate simulation output with corresponding sets of input variable conditions.
(5) Discretize the input and output data, tabulate the results and use them to generate a conditional probability table using the same method described for observed data.

There are several important issues to consider when using a model to generate simulations for use in a CPT. Uncertainty associated with the formulation of the model will not be explicitly accounted for in the BN. Results generated by the model for conditions outside of the model calibration and validation data range will add to unreliability in the BN. Often, large amounts of data are necessary to accurately calibrate a deterministic model. In this case, it may be more appropriate to generate probability distributions directly from the data, rather than to use a simulation model.

Other sources of information. In cases where data are sparse and no appropriate models are available, CPTs can be inferred from information obtained from experts and stakeholders. For example, expert judgment may be needed to estimate the probability of increased recreational use of a stream reach given improved fish habitat or the probability of degradation of surrounding areas given increased recreation. See Cooke (1991) *and* Meyer & Booker (1991) for methodologies for eliciting probabilistic information from individuals. When no expert judgment is available for the needed CPT then equal odds are used (e.g. $P(a_1|B) = 0.50$, $P(a_2|B) = 0.50$).

Depending on its number of nodes, a single BN may require estimates of several CPTs. Each of these may be derived using any one of the approaches presented here. For example, in a dam management BN, a CPT for streamflow given different dam release plans could be estimated from observed data; a CPT for flooding given different states of streamflow might be derived from a flooding model; and a CPT for economic impact given flooding might be estimated through expert judgment. In this way a BN provides a framework for integrating all relevant variables in the system using the best available information for each inter-variable relationship.

Model validation

A completed BN should be validated using independent information when available. However, this can be a challenge when the BN CPTs were derived from sources other than observed data or when no new data becomes available for assessing the BN model. Marcot *et al.* (2001) created BNs using expert judgment and validated the BN models using independent assessment of probability distributions by third-party experts. In some cases, the best or only available validation option may be to make decisions in the watershed and compare the results to those predicted by the BN model. This would be a suitable approach in cases where adaptive management is prescribed. At a minimum, a sensitivity analysis that considers the uncertainties in the BN model should be conducted.

This generic approach to developing and using a BN for watershed management should be applicable to a variety of problem types such as total maximum daily load (TMDL) implementation, integrated watershed planning and management, pollutant trading and assessing the impact of river management on endangered species. In the remainder of this paper, a case study on the application of the approach is presented with a BN analysis and results.

EAST CANYON RESERVOIR CASE STUDY

Case study overview

East Canyon Reservoir (ECR) in northern Utah, USA has experienced a dramatic decrease in recreational use over the past several years due to reductions in fish populations. The State of Utah Department of Environmental Quality (DEQ) has identified one of the causes of this problem as excess phosphorus entering the reservoir through East Canyon Creek, resulting in increased algal growth and subsequent eutrophication (low levels of dissolved oxygen) (Judd 1999). Phosphorus concentrations in East Canyon Creek have been determined to be in violation of the legal limit streams, placing this water body on the state's list of impaired waters (Utah DEQ 1998). The challenge faced by DEQ is to identify sources of phosphorus in East Canyon Creek and select management alternatives to control these sources in an economical manner.

Figure 3 shows the East Canyon drainage, dominated by East Canyon Creek which flows north approximately 26 km (16 miles) from Kimball Junction into ECR. ECR is the sink for surface and ground water flows from Park City, Kimball Junction, Jeremy Ranch and rural areas in the Wasatch Mountains, east of Salt Lake City and Bountiful, UT, USA. The Snyderville Basin wastewater treatment plant (WWTP) is the only major phosphorus point source in the drainage.

ECR hosts a state park and has historically supported a high quality cold water fishery. In recent years water quality and fish habitat in ECR has deteriorated and recreational visitation has decreased from 300 000 visitor-days/yr to about 80 000 visitor-days/yr.

Analysis of WWTP releases and streamflow data reveal that, during late summer, the WWTP contributes a large percentage (as high as 80%) of the flow in the creek. Also, the WWTP is the only major phosphorus point source. At the time of this study, the Utah Department of Environmental Quality was exploring new limits on phosphorus loadings from the WWTP. The available physical and chemical phosphorus removal technologies that would have to be implemented to attain these limits are very costly. As a result, the superintendents of the WWTP have challenged the State of Utah's position that restricting phosphorus in the plant's effluent will improve conditions in the stream and reservoir.

In addition to the WWTP, phosphorus also enters East Canyon Creek from non-point sources in the watershed headwaters. For the purpose of this case study, headwaters are considered to be in the Kimball Junction area near the intersection of the highways Interstate 80 and Utah 65. Non-point sources of phosphorus in the drainage include septic systems, grazing lands, camp grounds, golf courses, residential development and recreational reservoir use.

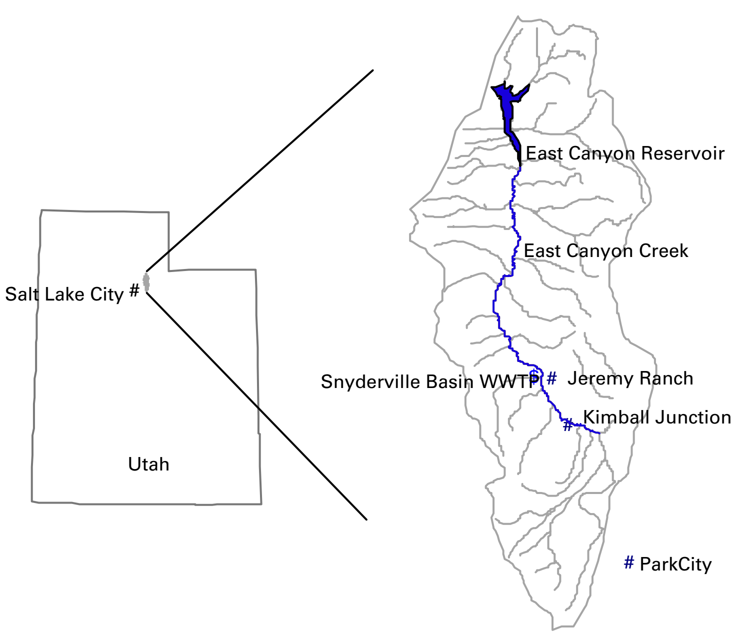

Figure 3 | East Canyon Creek watershed in northern Utah.

ECR BN MODEL DEVELOPMENT

Problem definition

Identify management endpoints

The goals of the management of point and non-point source phosphorus are: 1) decrease the risk of not meeting the legally required phosphorus limit in East Canyon Creek and 2) increase the probability of improved recreational use and revenue at ECR State Park. BN nodes associated with these management endpoints are shown in Figure 4 as *REV_RS* (revenue generated at the reservoir) and *PH_ST* (phosphorus concentrations in East Canyon Creek).

Identify management alternatives

The number of potentially acceptable and viable management options that can be implemented in the ECR watershed is limited. Specific management options defined by the DEQ for management of phosphorus in ECR include: 1) increase the level of treatment at the WWTP and 2) reduce non-point source loading in the watershed headwaters. BN nodes associated with these management alternatives are shown in Figure 4 as *OP_TP* (management options at the WWTP) and *OP_HW* (management options in the watershed headwaters).

The WWTP has been operating with biological treatment since 1992. This has resulted in a marked reduction in phosphorus concentrations in the WWTP effluent. In Table 1, *OP_TP* Alternative B ("Status quo") represents current conditions. Conditions at the WWTP prior to the use of biological treatment of wastes are represented by *OP_TP* Alternative A ("No bio. treatment"). Alternatives C and D represent two specific treatment technologies that can be installed at the WWTP. The first (Alternative C) is targeted to reduce effluent phosphorus to 0.10 mg/L and the second (Alternative D) is targeted to reduce effluent phosphorus to 0.05 mg/L. Management alternatives in the watershed headwaters (*OP_HW*) include "Status quo" (Alternative A) and "Reduce non-point" (Alternative B).

Identify critical intermediate and exogenous variables

Table 2 shows a list of all of the key variables for this study with a brief description and the variable type. The BN graph in Figure 4 shows the interactions between these variables grouped by geographic location and variable type. The only exogenous variable, season (*SEAS*), is the primary driver for headwater streamflow (*FL_HW*) and WWTP effluent flow (*FL_TP*). These variables are also directly impacted by the management alternatives at the WWTP (*OP_TP*) and in the headwaters (*OP_HW*). The costs associated with the management alternatives are shown as outcomes of the management alternative nodes (*CO_TP* and *CO_HW*). Phosphorus concentrations at the WWTP (*PH_TP*) and phosphorus

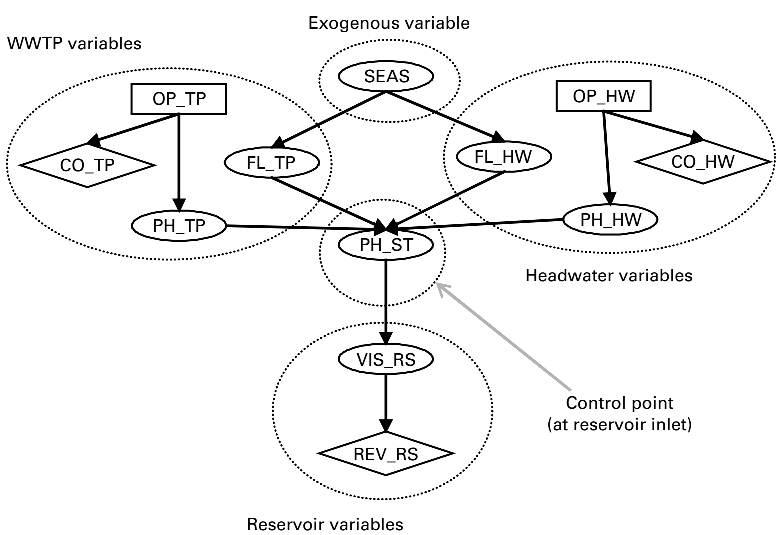

Figure 4 | East Canyon Creek BDN for phosphorus management.

Table 1 | Options and costs associated with phosphorus management in the ECR BN

Decision variable	Alternative A	Alternative B	Alternative C	Alternative D
WWTP options (OP-TP)	No bio. Treatment \$0	Status quo \$0	Target <0.10 mg/L \$5000,000	Target <0.05 mg/L \$10,000,000
Headwater options (OP-HW)	Status quo \$0	Implement BMPs \$2000,000	N/A	N/A

Table 2 | Critical variables for phosphorus management in the ECR BN

Variable name	Description	Type
OP_TP	Available management options at the WWTP	Decision
OP_HW	Available management alternatives in the headwaters	Decision
SEAS	Exogenous forcing variable related to climate conditions	Exogenous
PH_ST	ECR inlet phosphorus concentration	State
PH_TP	WWTP phosphorus concentration	State
PH_HW	Headwater phosphorus concentration	State
FL_TP	WWTP streamflow	State
FL_HW	Headwater streamflow	State
VIS_RS	Reservoir visitor-days	State
REV_RS	Revenue to the state and local community from recreational reservoir use	Utility
CO_TP	Cost to the WWTP anticipated under various management options	Utility
CO_HW	Cost for reduction of phosphorus concentration in the headwaters through the implementation of specific best management practices (BMPs)	Utility

concentrations in the headwaters (*PH_HW*) are both dependent on the selected management alternatives. The critical endpoint variables are East Canyon Creek phosphorus concentration at the ECR inlet (*PH_ST*) and revenue to the state and local community as a result of recreational reservoir use (*REV_RS*).

Establish discretization states for variables

The variables in the ECR BN were discretized into specific states including “High” and “Low” for streamflow variables; “High”, “Medium” and “Low” for headwater phosphorus concentration; five distinct states for WWTP phosphorus concentration; three states for East Canyon Creek phosphorus concentration and three states for the variable *VIS_RS* (visits to the state park at ECR). The specific states selected for each variable are described in a later section on model inference.

Identify data sources

Several data and information sources were identified to populate the probability distributions for the ECR BN. These include streamflow and WWTP effluent records, in-stream phosphorus concentration observations and information regarding recreational use of ECR. An existing water quality simulation model developed by Stevens (2000) using QUAL2E (Brown & Barnwell 1987) was also identified.

Plan for the use of probabilistic results

A key management endpoint in this study is *PH_ST*, in-stream phosphorus concentrations at the inlet to ECR. As noted previously, the State of Utah has established a legal in-stream phosphorus concentration criterion at 0.05 mg/L. The language that defines this limit does not allow for violations, even very low frequency violations. Rather, it would suggest that a stream is only satisfactory if it has a 0% chance of violation. However, as the results of this case study show, there is no set of management alternatives that reduces the probability of violation to 0. Therefore it was decided to present results in terms of the probability of exceedance of the limit, allowing DEQ to interpret this according to their needs.

Model inference

Cost of management options

Costs associated with management of the WWTP (*CO_TP*) are dependent on WWTP management (*OP_TP*) and costs associated with headwater management (*CO_HW*) are dependent on headwater management (*OP_HW*). In the BN model, these costs are stored in a "utility table". A utility table shows the utility (cost, benefit or other measure) of every combination of states of its parent node. Table 1 shows the utility tables for both decision nodes.

The estimated cost of upgrading the WWTP to target 0.10 mg/L and 0.05 mg/L phosphorus is $5 million and $10 million, respectively. These values were obtained from the WWTP superintendent based on the current market cost of each treatment alternative. Non-point source reduction in the headwaters of the East Canyon drainage will include a significant amount of riparian restoration, estimated by DEQ to cost approximately $2 million.

Streamflow

Assuming that flows from the WWTP are independent of the type of treatment used and that headwater streamflow is independent of non-point source management, the flow variables, *FL_TP* and *FL_HW* can be defined as only dependent on season (*SEAS*). These relationships require estimates of two CPTs, $P(FL\_TP|SEAS)$ and $P(FL\_HW|SEAS)$.

Daily records of flow releases from the Snyderville Basin WWTP between May 1992 and September 1996 (1614 records) were used to estimate $P(FL\_TP|SEAS)$. The data range from 0.031 m^3/s to 0.158 m^3/s with a median of 0.059 m^3/s, as shown in Figure 5. The data were categorized as "High" and "Low" using the median as a breakpoint so that an equal number of observations occur in each category. A CPT for $P(FL\_TP|SEAS)$ was computed using these states and is shown in Table 3.

Headwater streamflow (*FL_HW*) was defined as streamflow immediately above the WWTP. Daily streamflow values at this location were estimated by subtracting daily WWTP flows from data collected at the USGS Big Bear Hollow gage station immediately downstream of the WWTP. The resulting estimated streamflow ranges from near zero to over 14 m^3/s. These data were categorized as "High" or "Low" using the 10th percentile value (0.15 m^3/s) as a breakpoint to accentuate the low flow conditions, when the streamflow is dominated by WWTP inputs. The resulting seasonal CPT (Table 4) highlights the fact that the lowest streamflow in East Canyon Creek occurs in summer. This suggests that there is most likely to be a negative impact from undiluted WWTP phosphorus loads during the summer months.

WWTP phosphorus

WWTP effluent phosphorus concentration, *PH_TP*, is dependent on WWTP operation, *OP_TP*. Eight years of phosphorus concentration data at the WWTP (see Figure 6) were used to derive a CPT for $P(PH\_TP|OP\_TP)$ under each management alternative (see Table 5). Conditional probabilities for the management alternatives, "No bio. treatment" and "Status quo," were estimated from historical records of effluent total phosphorus concentrations from the WWTP. Probabilities for $P(PH\_TP|OP\_TP =$ *"No bio. treatment"*) were derived from 75 observations taken between February 1991 and July 1996. In August 1996, biological phosphorus removal was implemented at the

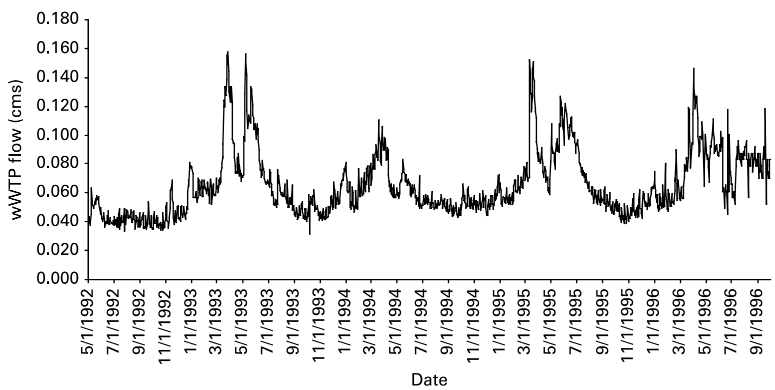

Figure 5 | WWTP effluent flow rate.

WWTP. This condition is representative of the "Status quo" alternative. Probabilities for *P*(*PH_TP*|*OP_TP* = *"Status quo"*) were derived from 45 observations of *PH_TP* taken between August 1996 and December 1998.

Conditional probability distributions for alternatives C and D were challenging to estimate because there is no prior experience at the Synderville Basin WWTP with either of the proposed technologies. At the present time, only a few wastewater treatment plants have implemented physical and chemical treatment technologies with an endpoint of 0.10 or 0.05 mg/L total phosphorus. Probability distributions for these alternatives were inferred from phosphorus effluent records from two similar WWTPs. These facilities both have treatment technologies installed with target phosphorus concentrations of 0.07 mg/L. Approximately 2200 observations taken at these facilities from 1990 to 1999 were scaled by 0.10/0.07 and 0.05/0.07 to represent likely effluent concentrations under alternatives C and D, respectively. These estimated datasets were then used to derive probability distributions for *P*(*PH_TP*|*OP_TP* = *"Target* < *0.10 mg/L"*) and *P*(*PH_TP*|*OP_TP* = *"Target* < *0.05 mg/L"*).

Headwater phosphorus

Headwater phosphorus concentration is conditioned on the selected headwater management alternative. Figure 7 shows phosphorus concentrations in the East Canyon Creek headwaters for 1979–1999. These data were used together with projections of reductions due to non-point source management to estimate a CPT for *P*(*PH_HW*|*OP_HW*). A 50% reduction in phosphorus concentrations was assumed under the non-point source management alternative using an estimate provided by DEQ.

Historical headwater phosphorus concentrations above the WWTP vary between 0.005 mg/L and 0.530 mg/L. The distribution of these data is shown in Table 6. Under status quo conditions, 35% of headwater concentrations were < 0.05 mg/L. This suggests the probability that the legal

Table 3 | CPT for *P*(*FL_TP*|*SEAS*)

	WWTP flow (*FL_TP*)	
Simulation season (*SEAS*)	**High**	**Low**
Winter	69%	31%
Spring	79%	21%
Summer	34%	66%
Autumn	18%	82%

Table 4 | CPT for *P*(*FL_HW*|*SEAS*)

	Headwater flow (*FL_HW*)	
Simulation season (*SEAS*)	**High**	**Low**
Winter	95%	5%
Spring	97%	3%
Summer	80%	20%
Autumn	91%	9%

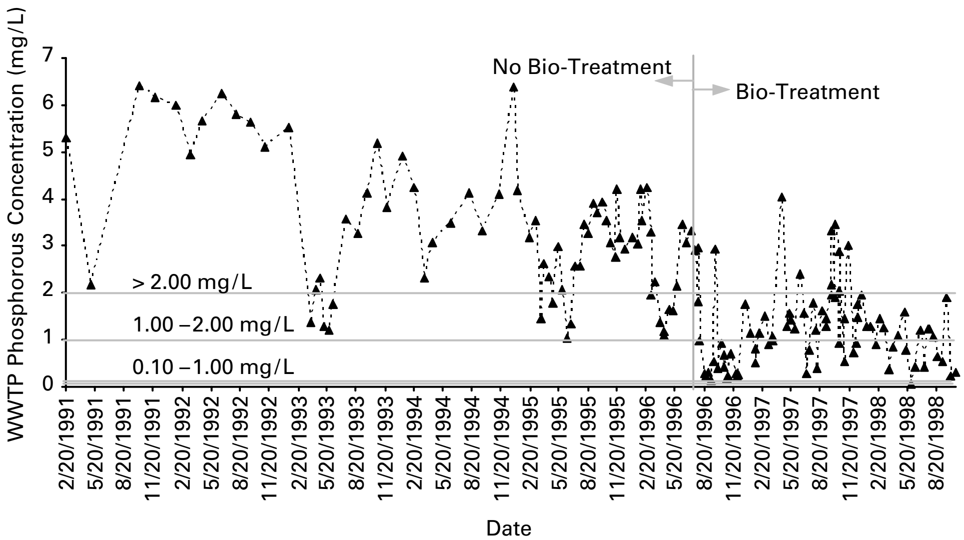

Figure 6 | WWTP effluent phosphorus concentration.

Table 5 | CPT for $P(PH\_TP|OP\_TP)$

	WWTP effluent phosphorus (mg/L) (*PH_TP*)				
WWTP management (*OP_TP*)	**<0.05**	**0.05–0.10**	**0.10–1.00**	**1.00–2.00**	**>2.00**
A. No bio. treatment	0%	0%	0%	20%	80%
B. Status quo	0.1%*	1%*	46%	39%	13%
C. Target < 0.10 mg/L	34%	42%	22%	1%*	0.1%*
D. Target < 0.05 mg/L	77%	15%	7%	1%*	0.1%*

*Although these small percentages were not observed in the raw data they were included as allowance for potential plant upsets.

limit for phosphorus is being violated 65% of the time, even without WWTP contributions.

East Canyon Creek phosphorus concentration

Phosphorus concentration in East Canyon Creek at the inlet to ECR (*PH_ST*) is a function of the flow variables (*FL_TP*, *FL_HW*) and the phosphorus concentration variables (*PH_ST*, *PH_TP*). The conditional probability distribution required here is $P(PH\_ST|PH\_TP, PH\_HW, FL\_TP, FL\_HW)$. A deterministic simulation model (QUAL2E) was used to estimate this CPT. QUAL2E was chosen because of its well-established uncertainty analysis module, QUAL2E-UNCAS, and because a model of the East Canyon Creek drainage using QUAL2E had already been developed by Stevens (2000) and was readily available to be used. This fits well with the proposed BN analysis scenario where all readily available data and information sources are used to develop and populate the BN.

The East Canyon Creek QUAL2E model was used to generate 16 000 Monte Carlo simulations. In these simulations, each of the four input variables (*PH_TP*, *PH_HW*, *FL_TP*, *FL_HW*) were varied over the full range of observed and expected values. A subset of model parameters were also allowed to vary within their specific acceptable ranges, as documented in Brown & Barnwell (1987). After each model simulation, the value of the four input variables and the resulting in-stream phosphorus concentration was recorded.

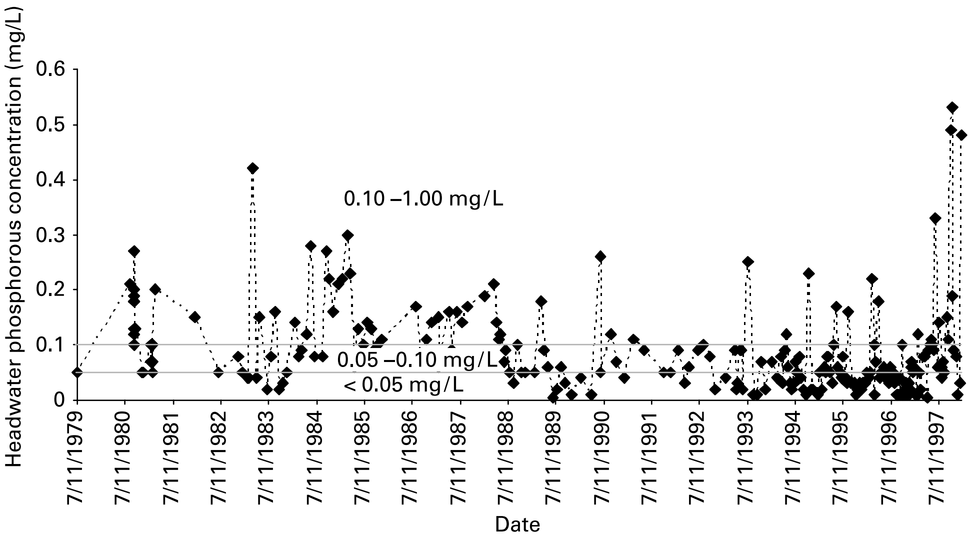

Figure 7 | Phosphorus concentrations in ECC above WWTP.

Table 6 | CPT for *P*(*PH_HW*|*OP_HW*)

Headwater BMP (*OP_HW*)	**Headwater total phosphorus (mg/L) (*PH_HW*)** Low (<0.05)	Medium (0.05–0.10)	High (0.10–1.00)
Status quo	35%	34%	31%
BMP implementation	60%	24%	16%

This resulted in a data set with 16 000 simultaneous observations from which the required CPT was inferred using the approach outlined previously in this paper.

The CPT for *P*(*PH_ST*|*PH_TP*, *PH_HW*, *FL_TP*, *FL_HW*) is a 60 × 3 table, giving the probability distribution across three states of *PH_ST*, "Low", "Medium" and "High", for all 60 possible combinations of the four predictor variables (e.g. "Low, Low, Low, Low", "Low, Low, Low, Medium", etc). In Table 7, a portion of this CPT is shown with predictor states indicated numerically. For example, "Low, Low, Low, Low" is indicated as "1,1,1,1" and "Low, Low, Low, Medium" is indicated as "1,1,1,2", etc.

Close examination of these conditional probability distributions shows consistency with what one might expect from the physical system. For example, during low-flow periods, streamflow is dominated by effluent releases from the WWTP. However, in high runoff periods, headwater flow dominates. In both cases, it is clear that streamflow directly impacts phosphorus concentration, and WWTP phosphorus discharge and headwater phosphorus concentration also directly impact the downstream phosphorus concentration.

Recreation endpoints

Additional management endpoints include visitor-days (*VIS_RS*) and recreational reservoir use revenue (*REV_RS*), requiring estimates of the conditional probability distribution, *P*(*VIS_RS*|*PH_ST*) and the utility function, *REV_RS* = *U*(*VIS_RS*). The challenge in deriving these probabilistic relationships is lack of data.

The Utah State Division of Parks and Recreation (DPR) was consulted to estimate *P*(*VIS_RS*|*PH_ST*). In the past decade, the number of visitors to the state park has declined from approximately 300 000 visitor-days/yr to less than 80 000, coinciding with a decline in the reservoir fishery (Judd, 1999). DPR has assumed that, if the eutrophication problem were solved, the number of visits to the state park facilities at ECR would return to the previous level. However, there is some uncertainty regarding this because of the concept of "recreational replacement". That is, people who stop using a park or facility tend to replace it with a different one, reducing the likelihood that they will return to the original when it is improved. A CPT for *P*(*VIS_RS*|*PH_ST*) was inferred from this anecdotal information and is shown in

Table 7 | Partial CPT for *P*(*PH_ST*|*PH_TP*, *PH_HW*, *FL_TP*, *FL_HW*)

PH_HW	*PH_TP*	*FL_HW*	*FL_TP*	In-stream phosphorus concentration (mg/L)		
				<0.05	0.05–0.10	0.10–1.00
…	…	…	…	…	…	…
1	2	2	2	100%	0%	0%
1	3	1	1	91%	9%	0%
1	3	1	2	46%	35%	19%
1	3	2	1	95%	5%	0%
1	3	2	2	57%	31%	12%
1	4	1	1	30%	38%	33%
1	4	1	2	0%	0%	100%
…	…	…	…	…	…	…
3	2	1	1	82%	9%	9%
3	2	1	2	73%	27%	0%
3	2	2	1	8%	53%	39%
3	2	2	2	7%	40%	53%
3	3	1	1	45%	33%	22%
3	3	1	2	16%	43%	41%
3	3	2	1	9%	47%	43%
3	3	2	2	2%	32%	66%
3	4	1	1	0%	43%	57%
3	4	1	2	0%	0%	100%
3	4	2	1	0%	18%	82%
3	4	2	2	0%	0%	100%
3	5	1	1	0%	0%	100%
3	5	1	2	0%	0%	100%
3	5	2	1	0%	3%	97%
3	5	2	2	0%	0%	100%

Table 8. The expected revenue from recreational use of ECR (*REV_RS*) is shown in Table 9 with values derived from a visitorship study in ECR conducted by Glover (2000).

Model validation

The BN analysis software package Netica (Norsys, 1998) was used to construct the ECR BN and conduct two types of sensitivity analyses. These analyses included the sensitivity of select variables to observations or findings at other variables and the sensitivity of select variables to changes in key probability distributions.

Netica provides a built-in function for the first analysis, allowing one to select an "inquiry" variable and several "test" variables. The function cycles through the nodes in the BN and systematically enters evidence or findings to simulate observing each state of each test variable. When a new set of observations is simulated, the resulting probability distribution for the states of the inquiry variable is recorded. Finally a single mutual information (MI) statistic is computed, indicating the variance in the inquiry variable that is explained by changes in the test variables (described in Norsys (1998)).

This analysis was used to identify those variables in the ECR BN that have the greatest effect on critical management endpoints. Specifically, *PH_ST* (phosphorus concentration at the reservoir inlet) was selected as the inquiry variable and all other upstream nodes in the network were selected as test variables. The analysis ranked the test variables in order of their influence on *PH_ST* from high to low as follows: *PH_TP* (MI = 0.447), *OP_TP*, *PH_HW*, *FL_TP*, *SEAS*, *OP_HW* and *FL_HW* (MI = 0.004).

These results suggest that in-stream phosphorus concentration is most sensitive to WWTP loadings and management options, while headwater streamflow and management options have the least impact. This is consistent with what one would expect in a point source dominated system and provides a first-cut assessment of which management options will have the greatest impact on management endpoints. Specifically, the assumption that headwater management would reduce phosphorus concentration by 50% was a liberal assumption based on a best guess from DEQ. The experience of the authors suggests that it is more likely that implementation of phosphorus management plans in the headwaters

Table 8 | CPT for *P*(*VIS_RS*|*PH_ST*)

In-stream phosphorus concentration (*PH_ST*)	Park visits (visitor-days) (*VIS_RS*)		
	<80,000	80,000–168,000	168,000–300,000
<0.05 mg/L	34%	56%	10%
0.05 – 0.10 mg/L	60%	25%	5%
>0.10 mg/L	97%	3%	0%

Table 9 | Utility table for the expected revenue for each possible state of *VIS_RS*

	Park visits (visitor-days) (*VIS_RS*)		
	<80,000	80,000–168,000	168,000–300,000
Expected revenue	$0	$1685,000	$4211,000

will yield somewhat less reduction in headwater concentrations. This being the case, and given that the management endpoint variable is not sensitive, even at the 50% reduction level, the analysis yields an argument for not investing further resources in considering headwater phosphorus management plans.

The second type of sensitivity analysis, investigating the impact of CPT estimates on management endpoints, focused on the CPT for *PH_ST*. This CPT is a central feature of the ECR BN and is singularly responsible for the high degree of sensitivity of *PH_ST* to *PH_TP*. The simulation model used to derive *P*(*PH_ST*|*PH_TP*, *PH_HW*, *FL_TP*, *FL_HW*) was calibrated and validated against water quality observations as described in Stevens (2000). Hence, one can assume that the resulting CPT is equally valid. However, it is useful to observe how sensitivity to variables changes given different estimates of this critical CPT.

Initially the CPT for *PH_ST* was "faded" using the Netica software. The fading function has the effect of moving the conditional probabilities for all states towards a uniform distribution. A 25% fading was applied to the *PH_ST* CPT and the sensitivity to findings analysis was repeated. This produced the same ordering of test variables as resulted from the original *PH_ST* CPT; however, the MI statistic for *PH_TP* dropped from 0.447 to 0.109. Similarly, when the *PH_ST* CPT was faded by 50% and 75%, the same ordering of test influence variables occurred with *PH_TP* MI values of 0.028 and 0.005, respectively.

For comparison, two additional formulations of the *PH_ST* CPT were tested including several random CPTs and a uniform CPT. In each case the new CPT was entered (replacing the original *PH_ST* CPT) and the sensitivity to finding analysis was repeated. As expected, the rankings of test variables using the random CPTs varied significantly between randomizations, and when a uniform distribution was used, the MI for each test variable was computed as 0 (i.e. no variable influenced *PH_ST*).

RESULTS AND DISCUSSION

Figure 8 shows the probabilities of states of all nodes in the network under status quo management and summer season conditions. This scenario results in a net benefit of $0.619 million/yr and has only a 28% chance of meeting the legally required in-stream phosphorus concentration. Under these conditions there is a 70% chance of continued low numbers of visitors at the state park. In this section, different combinations of management options and seasonal conditions were selected and the resulting probability distributions and costs and benefits were computed by the Netica software and compared to arrive at a final management recommendation.

Cost of management options

The total benefit of each management scenario was calculated as *REV_RS* - *CO_TP* - *CO_HW*. A summary of total benefit under each management scenario is shown in Figure 9. The value of *REV_RS* is also shown separately in

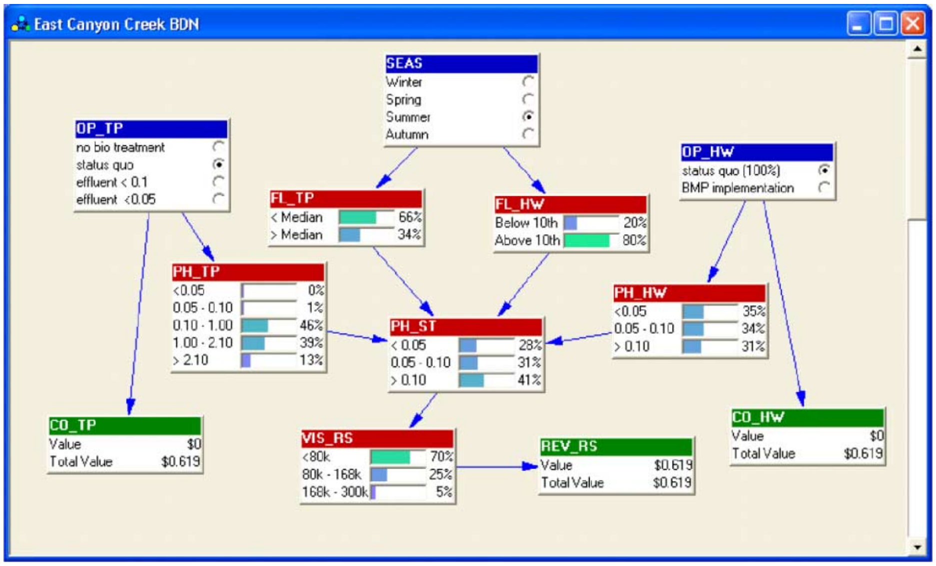

Figure 8 | Full ECC BDN showing probability distributions for status quo summer conditions.

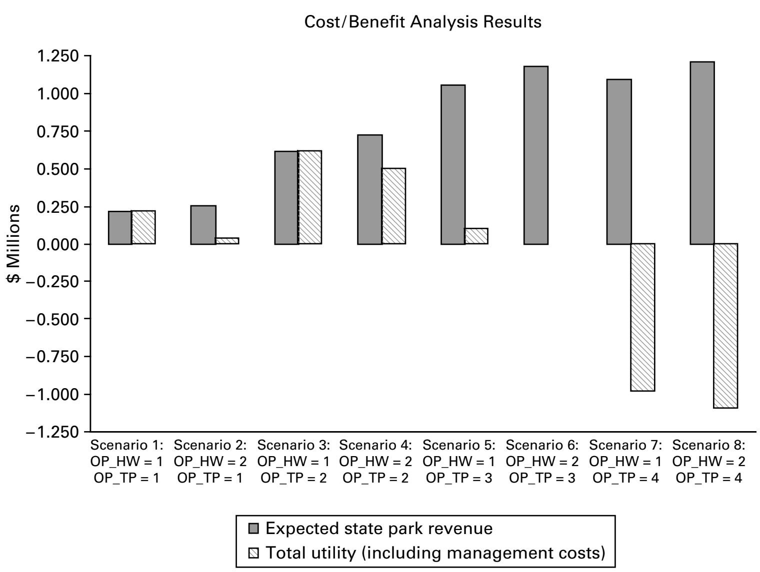

Figure 9 | Total costs and benefits resulting from each combination of management options given summer climate conditions.

this figure under each management scenario. The total benefit is negative in scenarios 7 and 8 because of the large costs associated with the management alternative, $OP\_TP = 4$ (targeting 0.05 mg/L effluent phosphorus). In the case of scenario 6, expected recreational use benefit is nearly equal to the cost of implementing the management decisions, so the expected total benefit is approximately 0. From a cost/benefit analysis point of view the most appealing option is Scenario 3, status quo in both the headwaters and at the WWTP. This scenario results in an expected total benefit of \$0.55 million/yr although it does not improve water quality or the recreational use of ECR.

In this case study, legal and political issues associated with degradation of ECR are motivating the decision analysis more than economics. If not, then the decision to maintain status quo at both the WWTP and headwaters would be chosen. However, given the other motivating factors, decisions in this system must be based substantially on the success associated with meeting water quality and recreational use goals stated as the primary management endpoints in the watershed.

Recreational reservoir use and phosphorus concentrations

A key endpoint goal of the analysis was to increase the probability of improved recreational use and revenue at ECR state park. Variables in the BN associated with this outcome are *VIS_RS* (visitor-days to the state park) and *REV_RS* (revenue realized at the state park). The probability of maintained or increased visitation at ECR (*VIS_RS*) under all combinations of management alternatives is shown in Figure 10, together with the risk of violating the legal limit for phosphorus. Considering these two endpoints, the optimal management scenario is scenario 8, non-point source reduction in the headwaters and improvement of the WWTP to target 0.05 mg/L phosphorus effluent. With respect to the visitation at the state park, the probability of same or improved conditions only increases from 57% to 58% by implementing the more stringent controls at the WWTP (scenario 8 versus scenario 6). This increase of 1% probability of improvement does not justify the significant increase in total cost of the scenario. Additionally, the increased revenue from recreational use of the reservoir under scenario 8 is only slightly better than under scenario 6.

From the point of view of recreational users of the state park there is not a clear need to choose scenario 8 over scenario 6. However, in the full decision-making context, and in light of the costs associated with scenario 8, it is important to consider the increase in probable benefit compared to the cost. While the cost–benefit analysis of scenario 6 shows nearly break-even conditions, scenario 8 is expected to have a net cost of over $1 million/yr. Therefore, from a recreational use point of view, the best choice would be scenario 6.

CONCLUSIONS

The Bayesian network analysis approach and case study presented here outline and illustrate a means for modeling complex watershed management decisions. The results of the case study show a clear choice of management alternatives that increase the probability of improved

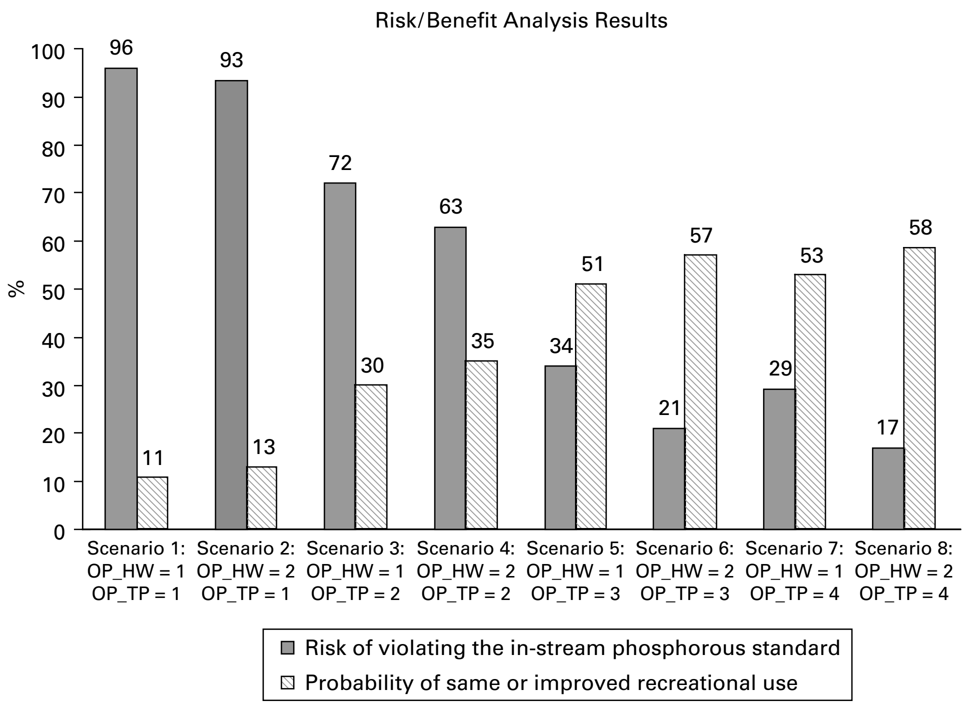

Figure 10 | Risk of violating the 0.05 mg/L total phosphorus water quality standard and probability of improving recreational use of ECR given summer climate conditions.

recreational use at ECR while reducing East Canyon Creek phosphorus concentrations at nearly no net cost. The recommended scenario uses a combination of improved headwater management practices and reduction in WWTP phosphorus concentrations through implementation of new technology that targets 0.10 mg/L. Together, this combination of management activities reduces the risk of exceeding the legal limit for phosphorus concentrations to 21%, and raises the probability of same or improved recreational use to 57% with an expected total benefit of $0.006 million/yr.

The BN framework serves as a structured means for capturing the probability that management activities will have the desired effect based on all of the available data and information relevant to the problem at hand. Deficiencies in the case study presented here are primarily associated with the lack of independent data to validate the model. In an adaptive management setting, one might collect additional streamflow, phosphorus concentration, recreation and revenue data and use it to further improve the CPTs used in the BN model. However, the ability to conduct a meaningful analysis in the absence of large quantities of data–even based in part on expert judgment–is a clear strength of the approach.

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