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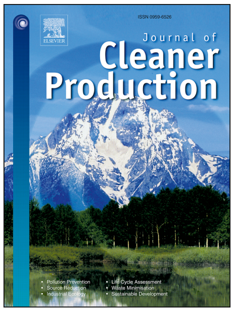

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Extreme events, water quality and health: a participatory Bayesian risk assessment tool for managers of reservoirs

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Abstract: Extreme weather events pose major challenges for the delivery of safe drinking water, especially in a country like Australia. As a consequence, a participatory Bayesian Network modelling approach was used to develop a risk assessment tool for estimating, and ranking, water quality-related health risks associated with extreme weather events. The model was developed for a large dam supplying a water treatment plant in New South Wales, Australia. This methodological approach addresses challenges associated with fragmented data (for model parameterisation) and parameter uncertainty by eliciting and integrating quantitative and qualitative data (including expert opinions) into a single framework. Key-stakeholders were engaged in developing and then refining separate conceptual models around the three critical parameters of turbidity, water colour and *Cryptosporidium sp.* These three conceptual models were then combined into a single conceptual model, which then formed the basis for the Bayesian Network model. The final risk assessment tool was able to quantify the sensitivity of the water treatment plant's efficacy (ability to supply high quality potable water) in response to different extreme event scenarios. Overall, landslip-related events were the most concerning for water quality-related health risks, but an emergent outcome was how the scenarios were ranked quite differently depending on the group, and expertise of the stakeholders' opinions used to run the model. Such tool can assist stakeholders for an effective long-term water resource management.

Keywords: System Thinking; Bayesian Networks; Water Treatment Management; Water Quality; Health; Extreme Events

Total words count: 10171

1 INTRODUCTION

1.1 Extreme weather events and water supply management

Extreme weather events pose a major threat to communities; weather-related disasters have already created significant challenges for organisations in recent years. For instance, the California drought during 2012-2014 caused water use restrictions and a quick reduction of the available groundwater (Famiglietti, 2014), as well as an increased number of wildfires (Yoon et al., 2015). In Brazil, a combination of rainfall deficiency, higher-than-average temperatures, increased population and water consumption resulted within a few months to severe drought conditions that left the main reservoirs in the São Paulo region with storage levels lower than 5% of the full capacity (Nobre et al., 2016).

A country particularly vulnerable to extreme weather events is Australia. Recent examples include the nation-wide Millennium drought from 1997 to 2008 (Heberger, 2011), the 2011 Brisbane floods (van den Honert and McAneney, 2011), cyclone Yasi in northern Queensland in 2011 (Beeden et al., 2015) and the 2009 "black Saturday" bushfires of Victoria (Cruz et al., 2012). These events have reduced the ability of water utilities to supply high quality potable water to consumers, or other bulk water clients due to the short- and long-term impacts of extreme events on the water quality at both pre- and post-treatment points in the system. In addition, extreme events are projected to change in magnitude and frequency over this century (IPCC, 2014), further exacerbating the pressures on water quality management. There are also large uncertainties associated with the timing and nature of specific future events and this uncertainty is a major contributor to the challenge of water management.

In this research study, the effects of these extreme weather events on key health-related water quality parameters were modelled for a large reservoir in New South Wales (NSW), Australia. Stakeholders from the water utility were involved in selecting the critical water quality parameters to be modelled, namely water colour, turbidity, and *Cryptosporidium sp*. The choice of this case study is motivated by the fact that the reservoir supplies one of the largest cities in Australia, and Australia itself is one of the countries mostly vulnerable to extreme weather events; however, the applied methodology can be transferred to other case-studies provided enough data is available.

1.2 Water colour, turbidity and Cryptosporidium

Water colour is one of the key parameters in drinking water reservoirs as it can affect the physical and biological properties of a whole lake or reservoir (Hakanson, 1993), as well as creating discolouration of the raw water redirected to the WTP. The colour of raw water is influenced by a particular low molecular weight hydrophilic fraction of the dissolved organic matter (DOM), which is generally recalcitrant to removal by coagulation. If not removed in the coagulation/filtration stages of treatment, it is of potential health concern as it will react with chlorine in the disinfection process leading to the formation of potentially carcinogenic trihalomethanes (THMs), one of the over 600 disinfection by-products currently reported in drinking water (Hrudey, 2009). However, the biggest issue with water colour is an increased coagulation demand, thus exacerbating in turn the risk of filter failure at the WTP and breakthrough, leading to a direct health risk.

Water turbidity is proportional to the quantity of solids suspended in the water. These solids may comprise clay, silt, inorganic/organic matter, plankton and other microscopic organisms (EPA, 1999). Suspended solids can provide food and protection from UV light for pathogens (Sinclair et al., 2012), and if not removed, they can reduce the disinfection efficiency of chlorine, increase the persistence of pathogens and promote their regrowth in the distribution system, elevating the risk of waterborne disease outbreaks (EPA, 1999; Tinker et al., 2008). Higher turbidity levels are therefore pathogen risk factors (Khan et al., 2013), typically associated with higher levels of disease-causing microorganisms such as parasites, viruses and some bacteria, which can cause cramps, diarrhoea, headache and nausea (Sarai, 2006). As a confirmation, turbidity has been shown to be correlated to contamination with *Giardia* and *Cryptosporidium* (LeChevallier et al., 1991) and serves as a surrogate measure for risk of contamination by these pathogens (Brookes, 2005).

Cryptosporidium is an intestinal protozoan pathogen that infects humans, domestic animals and wildlife worldwide, and has caused many waterborne outbreaks of cryptosporidiosis (i.e. typically a short-term acute infection affecting the intestine). *Cryptosporidium sp*. oocysts are often excreted in large amounts with the faeces of infected humans and animals (Graczyk and Fried, 2007), and can enter surface waters directly or through effluents and runoff from fields polluted by sewage sludge or manure (Graczyk et al., 2008; Mons et al., 2009) resulting in pollution of receiving waters. Importantly, these oocysts can remain infective for months in environmental waters and are highly resistant to chlorinated disinfectants (Betancourt and Rose, 2004). Therefore, microbial contamination is a growing concern for water suppliers, causing widespread outbreaks of these diseases (Putignani and Menichella, 2010). An example is provided by the 1993 waterborne outbreak of cryptosporidiosis in Milwaukee, where an estimated 403,000 residents became ill following an inadequate removal of *Cryptosporidium* oocysts in one of two municipal water treatment plants due to an ineffective filtration process (Mac Kenzie et al., 1994) and leading to almost $100 million of estimated medical costs and investment losses (Corso et al., 2003). Another example is provided by the Walkerton incident in Canada: an estimated 2,300 people became seriously ill and seven died from exposure to microbially contaminated drinking water in May 2000 (Hrudey et al., 2003). In the Australian context, high concentrations of *Cryptosporidium*, along with *Giardia*, were detected in the water supply system of Greater Metropolitan Sydney during the 1998 Sydney water crisis (McClellan, 1998), although it was not possible to determine the infectivity of the oocysts and zero cases of cryptosporidiosis were recorded, thus representing an example of contamination incident but not disease outbreak.

Determining the predictors of these three water quality indicators in a lake or reservoir is not straightforward because of the complexity of the interactions between limnological and meteorological variables, and the different ranges of scale involved.

1.3 The effect of rainfall and drought on colour, turbidity and Cryptosporidium

For water colour, Hakanson (1993) shows that there are a large number of factors involved in determining its level, some of which change on a daily or seasonal basis (e.g. temperature, precipitation), while others are related to the catchment characteristics (e.g. land use, lake morphometry). Generally, water colour is governed by the amount of dissolved and particulate material, such as algae or carbon. Previous studies found dissolved organic carbon (DOC) and water colour to be highly correlated (e.g. Pace and Cole 2002). Colour and DOC can be typically found in low concentrations in large lakes having a high residence time, however for lakes with extensive wetlands and peatlands the loadings are usually higher: in fact, soil is the largest terrestrial carbon pool (Hughes et al. 2013).

Rainfall is an important determinant of DOC and colour in surface water. Low rainfall periods are typically characterised by low colour. However, periods of heavy rainfall act to raise the colour levels through several mechanisms. The decrease in reservoir residence time during extreme precipitation events shortens the ‘processing time’ of the DOC, leading to higher aromatic compounds levels reaching the WTP (Ritson et al., 2014). Rainfall also affects the inflow conditions, which increases DOC loading into the lake after the rain infiltrates into the lower depths of the soil of the catchment (Hughes et al 2013). During extreme rainfall, new water pathways can be created leading to interaction with soil layers usually not heavily affected by runoff (Hongve et al., 2004). Therefore, high rainfall events following an extended dry period will tend to cause high DOC concentrations in lakes. For the scenario where the dry period coincides with a reduced storage volume (often as a result of low inflow conditions), the DOC entering the lake will be more concentrated within the lake/reservoir.

Rainfall-generated runoff and sediment resuspension within the lake contribute to increased suspended sediment loads over a short period of time (Bloesch, 1995; Longabucco and Rafferty, 1998) leading to elevated turbidity (Goransson et al., 2013). Additionally, in case of heavy rainfall events, the likelihood of landslides adjacent to the reservoir will be higher, thus leading to higher sediment loads and associated high turbidity; further, stratified reservoirs can (at least partially) mix during heavy rainfall events thus leading to elevated turbidity in the epilimnion, where the water is typically of better quality and thus drawn from (Bertone et al., 2015). Interestingly, high correlations between flow, turbidity and *Cryptosporidium* have been revealed after rainfall-runoff events in a multi-use catchment (Swaffer et al., 2014), which supports the hypothesis that turbidity can provide shelter for pathogens (EPA, 1999). Studies in the Three Gorges Reservoirs also confirmed that higher *Cryptosporidium* concentrations are recorded during the flood season (Xiao et al., 2013).

Rainfall events can cause damage and/or failure of transportation, electrical and communication infrastructure (Standford et al., 2014). If the resilience of the water supply system is limited, especially in small catchments, then it would be more prone to negative water quality impacts. Furthermore, heavy rainfall could lead to a number of sewer overflow events, leading to poorer water quality downstream (Khan et al., 2014). Again, resilience and preparedness of the water supply system is a key-factor in limiting the negative effects due to wet weather events. In the event that a superstorm, such as a tropical cyclone or low pressure system, hits the area of the water supply system, additional negative effects must be added to those associated to heavy rainfall only. These are mainly related to the very strong winds, which can cause damage to the infrastructure, especially the electrical and transmission parts (Liu et al., 2008). Proper maintenance and the presence of backup generators are essential to guarantee resilience and limit vulnerability.

1.4 The effect of fire

Another extreme event that represents one of the major threats to lake water quality in many areas around the world is the occurrence of wildfires. The duration of a fire, as well as the timing and magnitude of the following precipitation events, is a key-factor which will determine how much the water quality will be impacted (Canadian Water Network and Water Research Foundation, 2014). The negative effects of fire on water quality (e.g. peaks in turbidity, DOM, and also heavy metals and nutrients) might last for years, necessitating additional and costly treatment capacity beyond that required before the fire impacted (Canadian Water Network and Water Research Foundation, 2014). Smith et al. (2011) conducted an extensive review of the literature related to the impacts of bushfires on water quality; one of the associated consequences with fire is an increase in suspended solids and turbidity when high inflow events occur after the fire event has occurred. High water colour can also be an effect of bushfires due to ash. When a storm occurs soon after a fire, ash is washed into streams and reservoirs, and contains high concentrations of soluble inorganic material. The composition of ash is highly variable and depends on the type of vegetation burnt, the part of the plant burnt (bark, wood or leaves), soil type, climate, and combustion conditions (Someshwar, 1996; Demeyer et al., 2001). However, organic carbon has often been reported as a constituent (Demeyer et al., 2001; Goforth et al., 2005). For the 2003 bushfires in south-eastern Australia, Wasson et al. (2003) estimated that the amount of particulate organic carbon entering the Corin reservoir for the first 6 months after the fire was more than 5 times higher than the pre-fire rate.

1.5 Modelling environmental systems under high uncertainty

The risk of bushfires, extreme rainfall events or prolonged droughts is expected to increase in NSW due to climate change. Water quality management in this context requires a multi- and inter-disciplinary approach that is both holistic and probabilistic, to develop appropriate management strategies. Strong support and active participation from practitioners within the water industry, with experience of past extreme events and detailed understanding of the many facets of the system, is invaluable. Both qualitative and quantitative information about the system is also required. Traditional modelling approaches often deal poorly with such requirements (Fenton and Neil, 2008).

When the system being modelled presents a high degree of uncertainty and complexity, such as in ecosystems and environmental management, Bayesian Networks (BN) have become an increasingly popular modelling technique for risk assessment (Fenton and Neil, 2008), in different research fields, such as for the estimation of microbial risks for different end-uses of recycled water (Beaudequin et al., 2015), or sources of salinity in soil irrigated with recycled water (Rahman et al., 2015), or also the performance of manufacturing processes (Nannapaneni et al., 2016). The importance and usefulness of BN have been acknowledged in different fields such as artificial intelligence (Darwiche, 2009) and probability calculus (Conrady and Jouffe, 2015), and in general, BN have been recognised as “one of the most complete, self-sustained and coherent formalisms used for knowledge acquisition, representation and application through computer systems” (Bouhamed, 2015).

BN are a type of statistical model, specifically a probabilistic graphical model, and in general, provide a number of advantages compared to other models. Firstly, they are suitable for small or incomplete data sets: BN can easily handle missing or little data, and typically can yield good prediction accuracy even with a small sample size, provided that the model structure is well defined (Uusitalo, 2007). Also, it is possible to combine different sources of data: that is, where ‘hard’ data (survey, model and/or monitoring data) is not available, probabilities can manually be entered through expert knowledge. Thus hybrid sources of data (historical data and expert knowledge, or also other models’ outputs) can be used to overcome historical data limitations (e.g. where historical trends are not good predictors of future events) or to enhance the model performance (Uusitalo, 2007). As there is a growing need of incorporating community and stakeholders perspectives in natural (especially water) resources management (Lynam et al., 2007; Castelletti and Soncini-Sessa, 2007), BN provide a suitable modelling tool to integrate expert opinions with empirical data and potentially outputs from other models. BN also represent a suitable support tool for decision makers, as costs and risks associated to different management strategies can be easily assessed; additionally, the model simulation is typically extremely fast compared to some process-based models (Uusitalo, 2007). Especially in the water management sector, they are a good tool for dealing with informal institutional arrangements, such as different perceptions among stakeholders (Henriksen et al., 2007). In fact, the inconsistencies and attitudes found among different experts can be, in a Bayesian approach, a direct indicator of potential remedies (Hukkinen, 1993).

The choice of BN as a modelling tool also presents some challenges. For instance, continuous variables are not easily integrated within BN using expert knowledge to parameterise it. This often leads to nodes that are discretised with only a few states, often with qualitative terms (e.g. “high” and “low”). The disadvantage of this approach is that the states might provide only a coarse representation of the actual states for the node and qualitative terms can be difficult to define accurately (Uusitalo, 2007). Additionally, it may be difficult to convert experts’ opinions into probability distributions, especially when many states and/or many nodes are involved. It is important, for instance, to keep the BN simple, in order to restrict the amount of conditioning factors, as it has been proven to be cognitively difficult to think of conditional distributions with several conditioning factors (Morgan and Herion, 1990). However, often experts’ opinions can be considered reliable (Charniak, 1991). Finally, feedback loops, which could be informative in understanding how the system operates (Sahin et al., 2015) and which are present in the original conceptual model of this project, are not easily supported in BN. If they are extremely important in the modelled system, or they cannot be eliminated by changing the BN structure, then other model categories must be explored (Uusitalo, 2007).

Overall, BN have been increasingly applied in the past two decades for environmental modelling problems; a number of applications exist in the ecological modelling field (e.g. Marcot et al., 2001; Rowland et al., 2003; Little et al., 2004) but also in the water sector (e.g. Batchelor and Cain, 1999; Bromely et al., 2005; Rigosi et al.,

2015) and often they are applied to investigate the effects of climate change (e.g. Gu et al., 1996; Varis and Kuikka, 1997).

In this study, the authors also made use of a participatory model-building approach in order to conceptualise the models. Participatory approaches have been affectively applied in a number of studies (e.g. Figueiredo and Perkins, 2013; Kersten et al., 2015). Participatory modelling aims at involving stakeholders in one or more stages of the modelling process, from data collection through to model construction and use (Hare, 2011). Involving stakeholders increases the likelihood of deployment of the final developed decision support tool and involving experts for (conceptual) model development also facilitates the identification of key parameters and understanding of the system being modelled (Vennix, 1996). Participatory modelling has been applied in a number of water management or climate adaptation projects (e.g. Pahl-Wostl and Hare, 2004; Daniell et al., 2010; Richards et al., 2014). Those forms of participatory modelling supporting the development of conceptual models for social learning purposes can also be effectively adopted by water managers in order to provide support and aid future decision-making in the formal planning cycle (Hare, 2011).

Due to the proven ability of BN to deal with missing, uncertain, multidisciplinary data of different types, and the growing importance of applying participatory approach in the water resources management sector, a coupled participatory model building - Bayesian Networks modelling approach was used for this study to reliably predict colour, turbidity and *Cryptosporidium* concentrations in the water supply, and to rank different combinations of extreme events leading to unacceptable raw water quality.

2 MATERIAL AND METHODS

2.1 Research activities

The research activities were divided into a number of stages listed below:

1. *Problem scoping with the participants* (defining the problem/question, spatial domain, time frame, key issues); the objective is to gain a shared understanding of the problem.
2. *Parameters identification and definition* (predictors); in this case, the objective is to gain a shared understanding of the components.
3. *Elicitation of the expert knowledge* (mental models, cognitive maps) around the problem indicators linked with Step 1; the objective is to establish a participatory (shared) understanding of these systems based on the expertise. It includes collective understanding of the causal relationships and system structure that might help to explain the dynamic behaviour of the ‘system’ over time.

4. *Coalescing of the individual conceptual models into a single model* in order to integrate the separate models.
5. *Transformation of the coalesced conceptual model into a BN structure* – this is supplemented with scientific knowledge (literature) to help address potential gaps in the model arising from flawed mental models (systems theory).
6. *Identification of data needs / data availability* for each node (expert vs monitored data).
7. *Elicitation of conditional probabilities* for the BN, either based on experts' opinions or empirical data.
8. *Model testing* (sensitivity analysis to highlight potential management leverage points, scenario testing through top-down and bottom-up approaches).

Activities 1, 2, and 3 were conducted during a first experts' workshop. Activity 7 was completed through a second workshop with a larger group of stakeholders.

2.2 Project scoping and conceptual model development

An initial stakeholder project workshop was held in order to define the case-study sites, the key water quality parameters to be modelled and related level of service (LoS), and to populate the preliminary conceptual models. The first part of the workshop consisted in unstructured interviews, where the experts were asked to identify the parameters affecting the key-variables to be modelled, while the second part of the workshop consisted in "structured" interviews, meaning that the experts were asked to modify a preliminary conceptual model built based on the outcomes of the unstructured interviews. The key-variables are mapped in a causal network and through the participatory learning process this can be easily updated (Jakeman et al., 2006).

The model was developed for a large (2,000 GL) storage reservoir in NSW which is the main supply to a water treatment plant with treatment capacity of 3 GL/d. As mentioned before, Australia is one of the most vulnerable countries in terms of effects of extreme weather events. The specific reservoir was selected among the water bodies managed by the water utility part of this project, based on its relevance for the community for providing safe drinking water: it is, in fact, the largest reservoir of the region, primary source of drinking water for more than two million consumers. The agreed LoS for turbidity, water colour and *Cryptosporidium* were defined as: 40 NTU for turbidity, 60 CU^{400} for colour, and 10 IFA/10L adjusted for recovery for *Cryptosporidium*. In the following sections, by "LoS not satisfied" we refer to the ability to comply with the above thresholds.

As a first step, a table was created listing all the main factors directly affecting the three key-variables. Subsequently, by using a participatory approach, different stakeholders were engaged and consensus was reached on the identification and definition of each input variable; this is an important outcome of model building. The list of these variables is in the Results section. Finally, three separate conceptual models were developed, with the same participatory approach, to model the systems affecting turbidity, water colour and *Cryptosporidium* concentrations. Those three separate models were then merged together following the completion of the first workshop. As previously mentioned, participatory modelling, especially in an uncertain system, is essential as it helps identify the critical parameters and the main processes involved in the system to be modelled (Vennix, 1996).

2.3 Bayesian Network development

BN are directed acyclic graphs wherein each variable is presented as a node. Nodes that have input connections from other nodes ("parents") are labelled as "child" nodes. The strength of a connection (also known as conditional dependence) between a child node and its parent node(s) is quantified through probability distributions. There is one probability distribution per each combination of possible values of the parents. These probabilities are defined in the Conditional Probability Tables (CPTs) for each child node. The CPT of each node is a depiction of the associated uncertainty (Marcot et al., 2001), i.e. the higher the uncertainty, the wider the probability distribution; however, when more information/data (evidence) is available and uncertainty decreases, the probability distribution is updated, becoming narrower and the knowledge of the true value of the node increases. Populating the CPTs is one of the most delicate parts of BN development, but at the same time the most important and powerful feature compared to more soft decision support systems tools (Henriksen et al., 2007). Evidence is entered into the BN by substituting the *a priori* belief with observations (hard or soft evidence) or scenarios' values for a number of nodes (Chen and Pollino, 2012). Interactions between variables are clearly displayed and users can easily interrogate the reasoning behind the model output, thus providing a more transparent approach when compared to other "black-box" modelling techniques such as artificial neural networks (Chen and Pollino, 2012).

The comprehensive conceptual model developed as a result of the first workshop represented the foundation for developing a BN that would be used to assess the risk of impact of different extreme events on the LoS. The BN model structure was defined using the methodological framework of Chen and Pollino (2012), balancing model parsimony against model accuracy. This balance was addressed by (1) identifying and retaining only influential variables (influential on the key nodes) and (2) assigning a maximum of three states to those nodes requiring expert opinion for parameterisation. The latter point assists with producing CPTs that are relatively small and therefore more easily populated by expert knowledge. The BN was developed with the software Netica 5.18 (Norsys Software Corp.). Modifications from the conceptual model were performed to allow for a simpler structure, avoidance of feedback loops, and (generally) tractable CPTs.

After the structure of the BN was defined, a second stakeholder workshop was organised to refine the structure and populate the CPTs. Ten experts in different fields (e.g. water quality, water treatment, microbial risk, system configuration, risk management, operations management) attended the workshop and each was invited to populate all of the CPTs that underlie the BN structure. This activity took about 5 hours, following a 2-hour introduction. Subsequently, wherever available, historical data were used to populate the CPTs. Numerical data were available mainly for the environmental nodes of the BN. Due to different frequencies of data available for different nodes, the posterior probabilities were calculated separately for each parent-child node system, based on the available empirical data, on Microsoft Excel. The numbers were then transferred into the Netica model. For those nodes where historic numerical data were not available, expert opinions were kept for CPTs population.

3 RESULTS AND DISCUSSION

3.1 Input variables and conceptual model

Table 1 lists the main input variables affecting water colour, turbidity and *Cryptosporidium*, which were agreed during the first workshop. The correlation is positive if an increase in the input value implies an increase in the turbidity, colour and/or *Cryptosporidium* (i.e. a decrease in the water quality).

Table 1 – Nature of correlations between water quality predictors and colour, turbidity and *Cryptosporidium* as identified during the first stakeholder workshop

Input	Correlation with turbidity	Correlation with colour	Correlation with *Cryptosporidium*
Spill	+	+	+
Avoidance capacity	-	-	-
Use of alternative reservoirs	-	-	-
Ashes	+	+	NA

Runoff	+	+	+
Cryptosporidium runoff	NA	NA	+
Swamp runoff	NA	+	NA
Landslip events	+	NA	NA
Storage level	-	-	-

Firstly, there is *Spill*: if the dam is spilling (due to the storage level exceeding the full capacity), then the water quality is expected to deteriorate as the avoidance capacity is reduced due to the water moving from the bottom to the top of the dam wall (assuming the inflow coming as an underflow); the main factor affecting a possible spill is the storage level. *Avoidance capacity* on the other hand is linked to the presence, for instance, of multiple gates allowing the selection of the optimal intake depth from the dam. These structures reduce the risk of delivering raw water with very poor quality features to the WTP after, for instance, an extreme wet weather event. However, its usefulness is limited during lake circulation periods (e.g. winter turnovers) as the water quality is uniform throughout the water column. A similar management option was suggested to be the *use of alternative reservoirs*, connected to the same water filtration plant; provided the water quality is better than in the main reservoir, this option provides a temporary solution in case of unacceptable water quality in the main reservoir. Factors affecting the use of alternative reservoirs were identified as asset failure and contamination. An important natural factor which was identified was the presence of *ashes*: ash originating from bushfires and subsequently washed into the reservoirs through runoff will cause increased levels of colour and turbidity in the reservoir. Factors affecting their amount are mainly the presence of a fire in forested areas around the catchment and rainfall events following the fire. Also, in general, following a high rainfall event, increased *runoff* will bring sediments and organic matter which will increase the levels of turbidity and colour in the reservoir. In particular circumstances, the amount of *Cryptosporidium* will also increase. It was decided, for modelling purposes, to create two different variables (runoff and *Cryptosporidium runoff*) as the runoff affecting turbidity and colour is mainly influenced by the amount of rainfall, but in order for the runoff to generate high *Cryptosporidium* levels, other inputs (e.g. the presence of intensive livestock, onsite sewage, grazing, and the possibility of a sewage treatment plant overflow) can play an important role. Another special case of runoff, which would increase colour levels only, was identified as being *Swamp runoff.* Also, another indirect effect of rainfall events, which would increase the turbidity levels in the reservoir, is the occurrence of a *Landslip event.*

Finally, *storage level* was deemed to be an essential input variable. Typically, a higher storage level implies more water column stability, more dilution, and generally a better water quality. It increases the avoidance capacity (i.e. increased optimal intake depth selection options), but increases the risk of spill. It is affected mainly by runoff and direct rainfall.

Three separate conceptual models were developed for each parameter, i.e. turbidity, colour and *Cryptosporidium* (Figure 1) using the expertise and experience of the workshop participants and a review of the pertinent literature. Connections and nodes were defined in accordance to Table 1 and to the meaning and behaviour of the variables reported above; these connectors can have either a positive (i.e. when an increase in the input value implies an increase in the target parameter) or negative (i.e. when an increase in the input value implies a decrease in the target parameter) polarity. Additionally, these connectors are blue when an increase in the input value would imply a final lower risk of high levels of the key-parameters, and red in case it implies a final higher risk. The three separate models were subsequently merged together in a single, larger conceptual model. A feature of the models is that the main factors affecting water quality (as selected by the participants) were not only environmental (e.g. rainfall, drought, fires) but also related to the facilities of the water utility (e.g. variables such as avoidance capacity, alternative reservoirs, asset failure), land use (e.g. agricultural areas, forested areas, farms, grazing, intensive livestock) and even extreme human actions (such as intentional contaminations).

Subsequently, the conceptual model was converted to a BN according to the methodology discussed in the Materials and Methods section. CPTs were elicited during the second stakeholders' workshop.

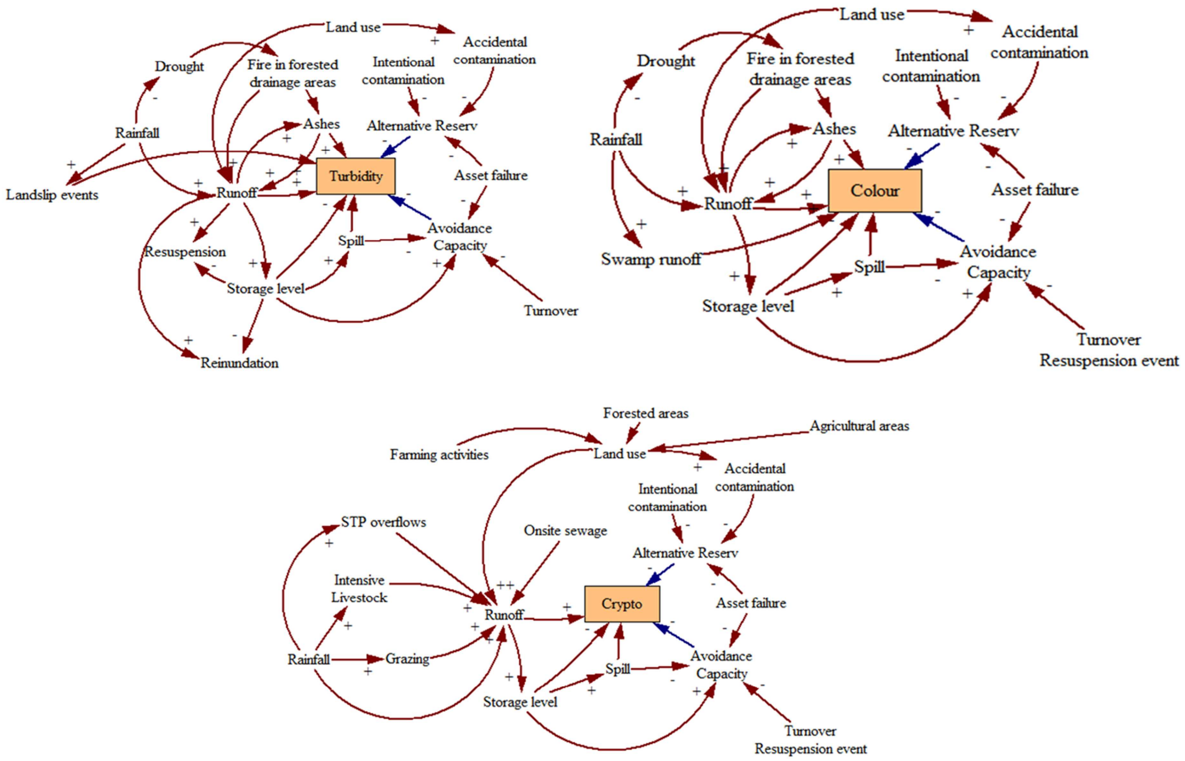

Figure 1 – The three separate conceptual models developed during the first workshop

3.2 Bayesian Network development and analysis

The final BN structure is presented in Figure 2. Firstly, a colour coding was used to cluster variables into different groups, such as environmental (i.e. blue nodes), land-related (pink), management-related (light green), targeted variables (dark green), or miscellaneous. As mentioned previously, numerical (empirical) data were available for most of the environmental (blue) nodes, whereas the other nodes required experts' opinions. Importantly, an auxiliary node "stakeholder" was created so that the model can be run according to the probabilities provided by each of the workshop participants, or by a group of them based on their different expertise. Four different groups were created for analysis purposes, based on a list of personal expertise provided by each stakeholder: (1) "Overall", where each stakeholder is assigned the same weight; (2) "water treatment"; (3) "science and water quality"; and (4) "management".

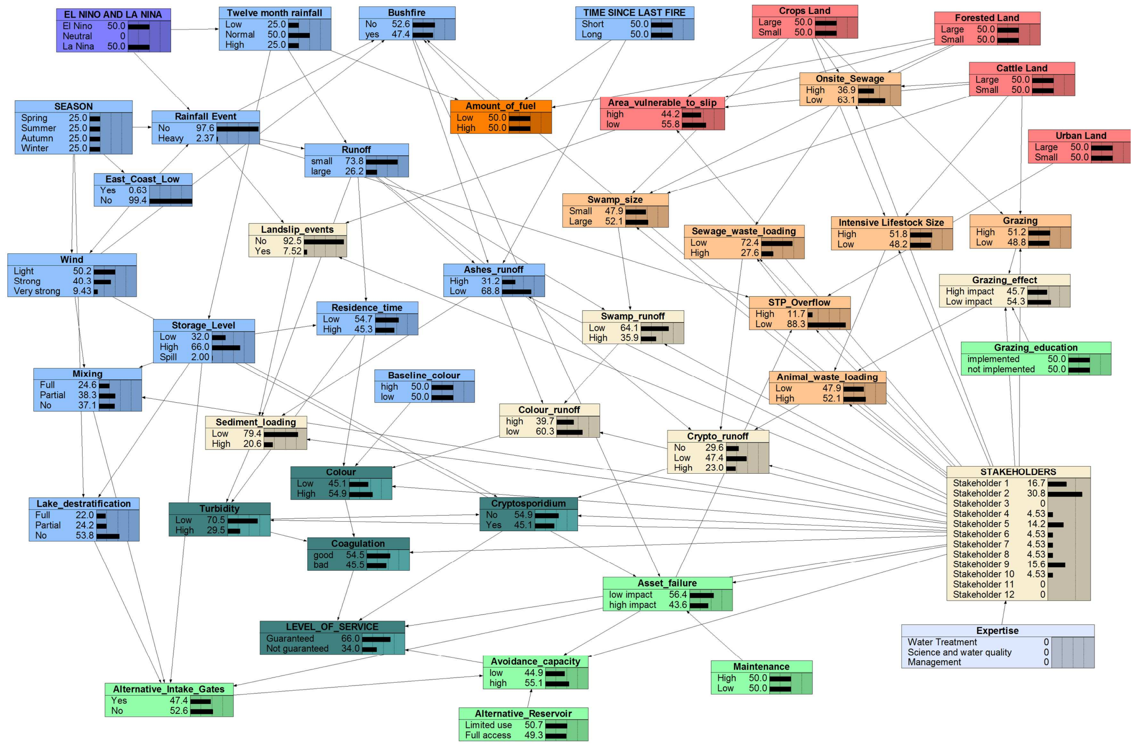

Figure 2 – Final BN structure

A sensitivity analysis was performed for the developed BN in order to identify the variables that are most influential on the risk of having LoS not guaranteed. In Figure 3, the BN was simplified in order to highlight the two most sensitive paths of the net. Overall, "*Cryptosporidium*" is the node that mostly affects the LoS (17.1% of the variance); "Coagulation" (i.e. how well the coagulation process is performed; affected by colour and turbidity levels) follows at 5.9%. Importantly however, the "Stakeholders" node, despite not being directly a variable of the modelled system, has a great influence (8.7%).

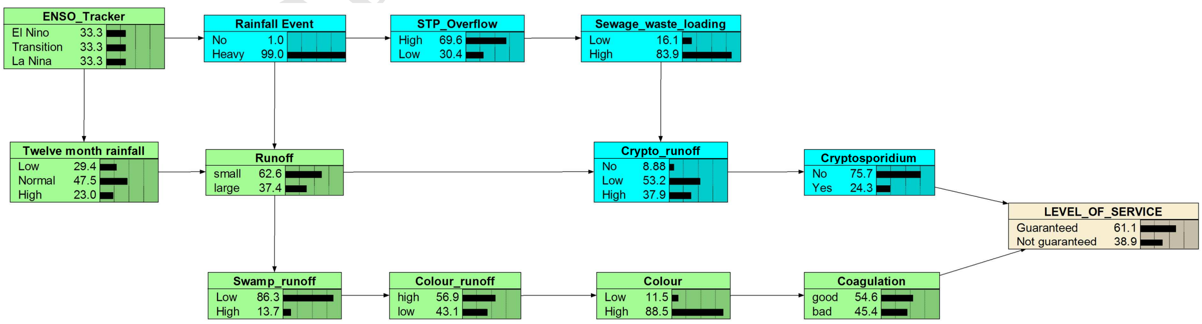

Figure 3 – BN's most sensitive paths

By applying a bottom-up approach and going back to the parentless nodes, it can be seen how the original trigger for high risk of poor LoS risks is rainfall – whether abundance or lack of. Thus bushfire, for instance, seems to play a less relevant role compared to, for instance, flood-related events in deteriorating the LoS.

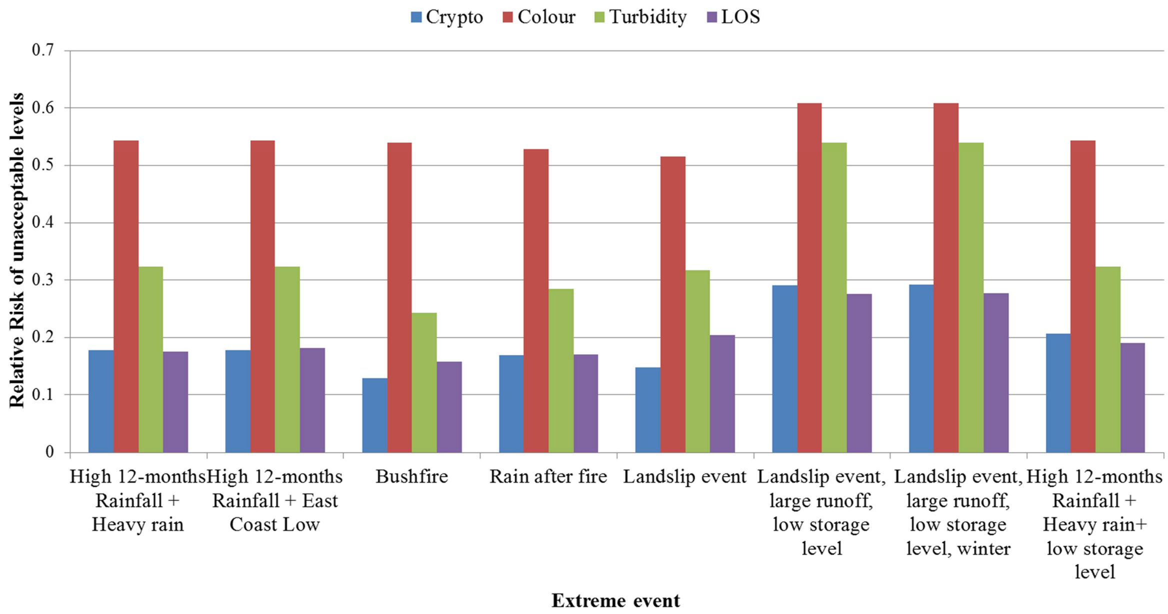

Figure 4 – Relative risk of unacceptable levels of *Cryptosporidium*, Colour and Turbidity in relation to types of extreme events

As a confirmation, Figure 4 represents the quantification of the relative risk associated to different extreme events; this was assessed by running the BN tool with different initial input configurations. By relative risk, we refer to the probability of delivering raw water with higher-than-threshold levels of the variable considered (i.e. colour, turbidity, or *Cryptosporidium*), as defined in Section 2.2. It can be seen how a bushfire, despite creating a quite high risk of elevated colour levels, would push the relative risk of LoS not being satisfied to only 0.158 (Table 2). Among the eight different scenarios analysed, a bushfire represents the least dangerous extreme event, in terms of risk of delivering water which does not guarantee the predefined LoS. If instead, a rainfall event occurred after a fire, then the relative risk of LoS not being guaranteed would climb to 0.17; however, it would be still a lower risk than those implied by other kinds of extreme events. This can be considered in line with existing studies, which have found how the impact of bushfire on water quality can be highly variable (Smith et al., 2011) and in some cases very small changes in e.g. turbidity were noticed (Sheridan et al., 2007). Flooding conditions instead would typically lead to higher turbidity and *Cryptosporidium* levels compared to a bushfire + rain event, and thus would create a higher risk for the water treatment. This is also in line with previous studies showing dramatic increases in *Cryptosporidium* (e.g. Kistemann et al., 2002) or presence of intense turbidity currents (e.g. Gelda et al., 2013) during extreme wet weather events. The three scenarios analysed in this case are ranked from number 4 to 6 in Table 2, with relative risk of not satisfactory LoS of, respectively, 0.19, 0.182 and 0.175. A prerequisite would be a very wet year prior to the extreme rainfall event, as this would imply a saturated catchment and thus much higher runoff. In addition, a low storage level, by reducing avoidance capacity, would even exacerbate the risk; however, due to the assumed wet year leading to the event, it is unlikely that the reservoir volume would be very low. Interestingly, the most critical extreme events for a water treatment management point of view would be associated to the occurrence of large landslides. This is with agreement with a number of studies arguing that landslides can represent the primary factor dominating the turbidity of reservoirs or rivers (e.g. Jordan, 2006; Sobieszczyk et al., 2007). In particular, the most critical event was found to be very heavy rain leading to (1) large runoff and (2) the occurrence of a landslip, occurring in winter (i.e. limiting the avoidance capacity), with a low storage level (i.e. limiting avoidance and dilution capacities). The large runoff itself is a source of turbidity since it can lead to the scouring of the fine sediment fraction at the bottom of the reservoir (Lin et al., 2011). This scenario would imply a relative risk of the LoS to be not satisfied of 0.277.

A landslip would create very high risk of elevated turbidity, which would become the leading critical parameter along with colour. It can be noticed that *Cryptosporidium* risk is always much lower, but the impact of high *Cryptosporidium* risk on the LoS would be higher due to the importance of this node, as discussed in relation to the sensitivity analysis. Importantly, it must be said that the effectiveness of the coagulation process is nonlinear in relation to turbidity and colour; that is, according to the stakeholders, raw water with both high turbidity and high colour might be easier to treat than raw water with high colour only (since the flocs are more stable) and thus leading to lower risk of poor LoS.

Table 2 – Extreme events ranking in relation to relative risk of LoS to be not satisfied.

Rank	**Rank colour**	**Rank Tb**	**Rank crypto**	**Event description**	**Relative risk LoS not satisfied**
1	1	1	1	Landslip event, large runoff, low storage level, winter	0.277
2	2	2	2	Landslip event, large runoff, low storage level	0.276
3	8	6	7	Landslip event	0.204
4	3	3	3	High 12-months Rainfall, Heavy rain, low storage level	0.190

5	4	4	4	High 12-months Rainfall, East Coast Low	0.182
6	5	5	5	High 12-months Rainfall, Heavy rain	0.175
7	7	7	6	Rain after fire	0.170
8	6	8	8	Bushfire	0.158

Regarding water management strategies aimed at reducing such risks, apart from the use of alternative reservoirs (which surely would avoid drawing, and attempting to treat, poor quality raw water, but would have operational and economic issues to be better assessed), the preferred option for the stakeholders was to have a high avoidance capacity. This is typically guaranteed through the potential of selecting the optimal intake depth according to the monitored raw water quality: typically, in the case of high turbidity, colour or *Cryptosporidium* levels, it is possible to find a better depth with lower concentrations of those key contaminants. However, in case of low storage level (i.e. only few intake gates under water, less options), lake circulation periods (i.e. uniform lake water quality), or spill (i.e. possible underflow of water moving from bottom to the lake to top of the dam wall, creating uniform water quality near the gates), the avoidance capacity can be quickly reduced and the risks for water treatment are perceived to be higher. On the other hand, the importance of maintenance, which could reduce the risk of failure of critical assets, was somehow considered less relevant than the variable intake depth option, with a typical risk reduction of only 0.1% in case of high maintenance planned. Similarly, other options such as grazing education, which could eventually reduce the risk of *Cryptosporidium* detection, had a lower influence on the final risk of poor LoS, as the land-use and management nodes of the network had a lower influence to the BN outputs, when compared to environmental variables (as proven by the sensitivity analysis).

3.3 Stakeholder effect on model results

These results presented so far are based on the conditional probabilities elicited from the overall pool of experts involved in the workshop process and supplemented by numerical data. However, the sensitivity analysis indicated that the area of expertise of a stakeholder was also a strong determinant of BN model behaviour (Figure 5).

Stakeholders with a water treatment (WT) background consistently provided probabilities leading to higher risks. The authors hypothesise that, due to their own everyday working activities and experience, they are more concerned and more aware of the consequences of extreme events. Managers (M) also typically provided higher than average probabilities of poor water quality, however in some cases (landslip-related events) these were lower than what was provided by the other stakeholders. Interestingly, managers would take flood-related events as the most threatening for the reliable operation of the WTP, with also bushfire-related events having more impact than landslide-related ones. Science and water quality (SWQ) experts provided conditional probabilities that reflected a more conservative approach, and the resulting probabilities were usually close to the overall (OV) average. As suggested by Hukkinen (1993), the presence of such inconsistencies among different experts can be a direct indicator of potential remedies: thus, better communication and knowledge-sharing between different stakeholders is recommended to improve the consistency of water treatment and decision-making, and to eventually devise more specific, targeted intervention strategies. It is in fact accepted that participatory modelling can be a support tool for the type of social learning currently being promoted for water resources management (Ridder et al., 2005). Moreover, a benefit of such process is the enhancement of communication between different stakeholders, researchers and the broader community (Jakeman et al., 2006).

Often the posterior probabilities calculated from empirical historic data were quite different from those provided by a number of stakeholders, due to possible misperceptions of the likelihood of a certain event. For instance, the probability of having an East Coast Low on a summer day in the Sydney area is, historically, only 0.3%; despite realizing the unlikelihood of such event, many stakeholders assigned a probability between 5% and 10%, which is considerably higher than the actual. This could also mean that there was not a clear understanding of the definition of certain nodes. One of the major difficulties that the authors encountered during the second workshop was the need for a large amount of time (due to the high number of nodes and CPTs to populate) dedicated for a thorough explanation and definition of each variable, and thus this represents one of the current limitations of the developed tool. However, the benefit of such approach is that is a continuous, iterative process and thus the CPTs can be updated in the future. What the Bayesian approach allows is to insert evidence as it comes available, thereby updating the posterior marginal probabilities over time.

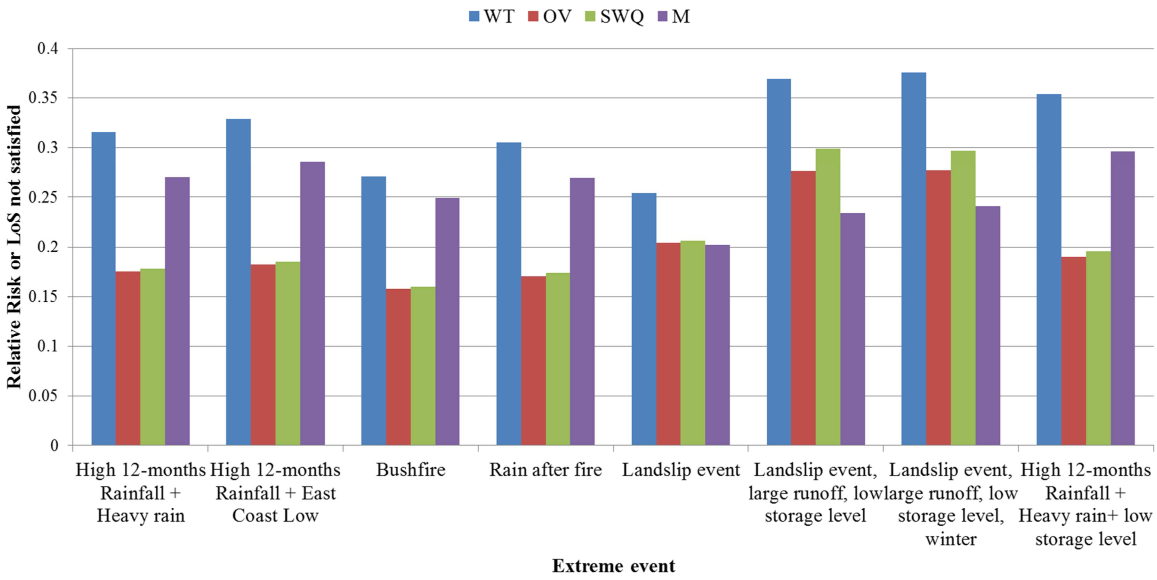

Figure 5 – Relative Risk of LoS to be not satisfied for different stakeholders' expertise: WT = water treatment; OV = overall; SWQ = science and water quality; M = managers.

In conclusion, despite a few issues with eliciting experts-based CPTs, from a systems perspective it is the structure of the system that is important (including polarity of cause-effect relationships). Understanding the structure of the system provides an understanding of the system behaviour (over time), which was captured in the conceptual model. Furthermore, the conceptual system structure was used as the basis of developing the BN structure, with the difference being the removal of the temporal (i.e. feedback) component, thus providing a snapshot in time tool. Importantly, although the CPTs might need further refinement, the BN structure, evolution of the conceptual models defined in accordance to the stakeholders' input through the participatory approach, is solid and comprehensive, and an important output of this study. CPTs can be updated at any stage thanks to the flexible Bayesian approach. In case the CPTs were good but the structure was not, updating the structure would imply updating the CPTs too; however updating the CPTs does not require updating the structure.

4 CONCLUSIONS

A risk assessment tool was developed to understand, rank, and manage the effects of extreme events, or a combination of them, on the ability of a water treatment plant to deliver high quality water to consumers. A participatory modelling approach was applied and a Bayesian Network was developed around the key parameters of turbidity, water colour and *Cryptosporidium*, as they also have potential negative health effects for water consumers. The conceptual model was built based on experts' input, and the BN was populated with posterior probabilities based on historical empirical data, and elicited from stakeholders wherever data were not available. Results show how a large runoff event leading to landslides during times of limited avoidance capacity would result in the most concerning set of conditions for the water treatment plant. However, certain specific groups of stakeholders indirectly ranked the extreme events differently: for instance, management people were more concerned about flood-related events or bushfires. In terms of water management strategies, the preferred option for reducing the risks from extreme events was found to be the retention of high avoidance capacity (i.e. the potential for optimal intake depth selection from the storage reservoir), which is related to a high storage volume, and to limited water circulation: because of climate change (leading to increased dry periods and thus more frequent low storage volumes, and increased extreme rainfall events bringing higher turbulence and mixing of the lake waters) the avoidance capacity might be, on average, much lower than in the past, which would require water managers to devise adaptation strategies to compensate for this.

The applied methodology proved to be effective for this water management application. It addressed the high levels of uncertainty and data limitations in the modelled system, and the engagement of a number of key stakeholders in defining and populating the models made the risk assessment tool more credible and more likely to be implemented within the organisation. Significantly, remarkable discrepancies were observed between the opinions of different groups of stakeholders; although this can be partially explained by misunderstandings about the definition of certain nodes, it is considered that improved communication and knowledge-sharing between these groups of people could be extremely beneficial for a more consistent routinely water treatment operation and management. Participation in this project actually served to facilitate improved communication between groups, particularly since there were multiple opportunities for information sharing through workshops and repeated rounds of consultation during model development.

The developed tool can be transferred and adapted easily to other water supply systems. Such tools can support and provide guidance to water utility managers on the most effective, scientifically based long-term plans for drinking water treatment operations under changing climate and exacerbation of extreme events.

Future work will focus on transferring and readapting the BN inputs to build a System Dynamics model able to numerically assess the magnitude and frequency of colour, turbidity and *Cryptosporidium* over-the-threshold events in the long-term and with different scenarios of population growth, water source selections and magnitude of extreme events. Also, further stakeholder engagement would allow for a refinement of the previously filled CPTs leading to a more consistent BN that can rely more heavily on expert information.

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Paper highlights

- A risk assessment tool for health-related water quality risks was created
- The model was developed for a large dam supplying a water treatment plant
- A participatory Bayesian Network modelling approach was used
- Extreme weather events are ranked based on the estimated risks