

Review

Applications of Bayesian Networks as Decision Support Tools for Water Resource Management under Climate Change and Socio-Economic Stressors: A Critical Appraisal

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Abstract: Bayesian networks (BNs) are widely implemented as graphical decision support tools which use probability inferences to generate “what if?” and “which is best?” analyses of potential management options for water resource management, under climate change and socio-economic stressors. This paper presents a systematic quantitative literature review of applications of BNs for decision support in water resource management. The review quantifies to what extent different types of data (quantitative and/or qualitative) are used, to what extent optimization-based and/or scenario-based approaches are adopted for decision support, and to what extent different categories of adaptation measures are evaluated. Most reviewed publications applied scenario-based approaches (68%) to evaluate the performance of management measures, whilst relatively few studies (18%) applied optimization-based approaches to optimize management measures. Institutional and social measures (62%) were mostly applied to the management of water-related concerns, followed by technological and engineered measures (47%), and ecosystem-based measures (37%). There was no significant difference in the use of quantitative and/or qualitative data across different decision support approaches ($p = 0.54$), or in the evaluation of different categories of management measures ($p = 0.25$). However, there was significant dependence ($p = 0.076$) between the types of management measure(s) evaluated, and the decision support approaches used for that evaluation. The potential and limitations of BN applications as decision support systems are discussed along with solutions and recommendations, thereby further facilitating the application of this promising decision support tool for future research priorities and challenges surrounding uncertain and complex water resource systems driven by multiple interactions amongst climatic and non-climatic changes.

Keywords: climate change; decision support tools; optimization-based approaches; scenario-based approaches; management measure categories; socio-economic stressors

1. Introduction

1.1. Contextual Background

Water resource systems are widely regarded as being under considerable threat in many regions across the world, often from the combined pressures of climate change, socio-economic stressors, and demands from multiple stakeholders [1]. Changes in precipitation, increased temperature and sea-level rise are major drivers of changes in water availability and water demand in these systems [2]. Interactions among these climatic drivers coupled with population growth and urbanization can lead to water scarcity, making it increasingly challenging for managers to satisfy growing water demands from multiple water users [3]. Where water resources are insufficient to supply socio-economic development and ecosystem functions, competitive behaviour among water use sectors can result [1], with considerable potential for conflict [3]. In such circumstances, it is important to identify appropriate, effective and efficient adaptive responses to alleviate these potential conflicts, and inform judicious trade-offs between competing demands [4].

Potential adaptation options have to be evaluated carefully to ensure that they are feasible, effective and efficient [5] as well as to avoid mal-adaptation, reduce risks, and the introduction of unnecessary intervention costs [6]. Adaptation measures for water resource management can take many different forms, depending on the context and objectives of a particular situation, so it is not surprising that several different approaches have been used to categorize the diversity of adaptation options and to assess their performance [4]. Adaptation options are frequently evaluated in terms of their costs, effectiveness, robustness and resilience across a range of current and anticipated future scenarios [5] for key physical, social, economic, and environmental drivers of the affected water resource system [7]. However, it is difficult to configure a consistent evaluation framework to support adaptation decision making for water resource management, because predicting the current and future responses of water resource systems to changes in multiple interacting drivers involves high levels of uncertainty and complexity. Given these challenges, evaluation approaches are needed, that can integrate empirical data, model simulations, and expert knowledge to facilitate selection of cost-effective, robust and resilient adaptation options within situational and budgetary constraints.

Bayesian networks (BNs) hold considerable promise as decision support tools for evaluating adaptation options for water resource management [8]. BNs can be configured as graphical decision support tools which use probability inference to generate “what if?” and “which is best?” analyses of potential adaptation options for water resource management, under climate change and socio-economic stressors [6]. A particular advantage of using BNs to inform water resource management is their capacity to integrate both quantitative data (e.g., field data and modelling results) and qualitative data (e.g., expert knowledge and stakeholder beliefs) to generate probabilistic predictions about the outcomes of potential adaptation options or policies [9]. The generation of probabilistic predictions is extremely valuable in devising management responses to scenarios of climate change and socio-economic development, which themselves come with an associated probability [6]. In addition, the ability of BNs to incorporate expert knowledge is particularly helpful for considering the uncertainty inherent in complex water resource systems, and for estimating costs and relative utilities of adaptation outcomes [6,8].

Several papers have reviewed applications of BNs in the broad context of environmental and water resource management. For example, Aguilera et al. [10] focused on the usage of BNs for modelling and informing the management of environmental systems generally. McDonald et al. [11] reviewed the usage of BNs in ecological risk assessments in freshwater and estuarine ecosystems, while Sperotto et al. [12] investigated the usage of BNs in climate change impact assessment for environmental management. Additionally, Phan et al. [13] reviewed the applications of BNs in water resource management across different water management domains and geographical locations, as well as considering the application of different knowledge bases for BN development. However, to date, no

reviews have evaluated the application of BNs as decision support tools for identifying appropriate adaptation options for water resource management under climate change and socio-economic stressors.

This paper presents the findings of a systematic quantitative literature review conducted to explore the applications of BNs as decision support tools for managing water resource under threats from climate change and socio-economic stressors. The review examines the different types of data (quantitative and/or qualitative) that have been used, whether optimization-based and/or scenario-based approaches are adopted for decision making support, and the different categories of adaptation measures evaluated in BNs for water resource management. Gaps are identified in the application of particular decision support approaches for evaluating different types of adaptation measures. Potential reasons for observed patterns of usage are suggested, and potential risks are discussed. Finally, possible solutions are suggested to enhance the efficacy of BNs for decision support in water resource management.

1.2. Bayesian Networks

A Bayesian network (BN) is a probabilistic graphical model consisting of a directed acyclic graph (DAG), which denotes dependencies and independencies between variables, and conditional probability tables (CPTs), which specify the relationships between those variables [9]. Each variable, defined as a node in the BN, has a set of states, and the probability of each state of a node is dependent on the states of the parent node(s). These probabilities are defined by the CPTs, which may be derived using qualitative and/or quantitative data [14]. Quantitative data refers to the measurable characteristics or fluxes in a system, and may include time-series data, such as river discharge, spatial data, such as household census data and the population within a region, or point data such as water quality conditions. Qualitative data or information includes expert opinion, stakeholder beliefs or some types of information derived from surveys and interviews [15].

There are three possible types of nodes in a BN: Chance or nature nodes, decision nodes and utility nodes which can be either discrete or continuous [9]. The BN can be used as a Decision Support Tool (DST) when decision nodes (management options) and utility nodes (costs and benefits of actions and outcomes) are included [16]. The DST can be applied to generate ‘which is best?’ (optimization-based) or ‘what if?’ (scenario-based) analyses of the performance of water resource management options [6]. The states of decision nodes can be used to depict possible management options. Decision nodes can also have an associated cost function that reports the actual or relative cost incurred in implementing each management option [9]. The states of response or target nodes(s) in the system can be used to depict different possible outcomes from implementing particular management options. Response nodes can have an associated utility function that reports the value (or utility) consequences which follow from each possible outcome state. Probabilities for the different outcome states under a particular management option follow from the inter-linkages between system variables as specified in the system’s CPTs. Value (or utility) consequences for the different outcomes can be specified in monetary or relative performance terms, reflecting their desirability [16]. The value delivered by implementing a particular management option can thus be expressed as the probability-weighted sum of the values (or utilities) of the different possible outcomes under that management option. From an economics perspective, this probability-weighted sum could be termed the expected utility delivered by the management option. If value consequences are expressed in monetary terms, a probability-weighted monetary benefit can also be calculated.

A BN which includes the decision node(s), and associated cost node(s), together with the response node(s) and associated utility node(s), can be considered as an optimization-based decision support tool (Figure 1a), because it can identify the management option which delivers the highest probability-weighted value relative to the cost incurred [9]. This BN configuration could provide a probabilistic cost and benefit-based optimization. Probabilistic cost-effectiveness of different management options can be evaluated by a BN with decision node(s), cost node(s), and a response node (without an associated utility node), by dividing the probability-weighted physical outcome (e.g., water availability in Figure 1a) for each management option by the cost of implementing that option [9].

Equivalent optimization functionality can be obtained by coupling a BN with decision node(s) and a response node, but without a cost or utility node, to external estimation of the economic costs of management options (for cost-effectiveness analysis), or to economic estimations of management costs, and economic valuations of the different output states (for cost-benefit analysis) (e.g., [17,18]). In contrast, a BN which only includes a decision node(s) and response node(s), without associated cost nodes and/or the utility node(s)—and without any coupling to external economic cost or value estimations—can be considered to provide scenario-based decision-making support, because it can evaluate probability-weighted physical outcome(s) (e.g., water availability in Figure 1b) for different management options, under different scenarios for key drivers of the system. However, a BN which does not include decision node(s), cost node(s) and/or utility node(s), and/or not scenarios can be considered as a predictive model only.

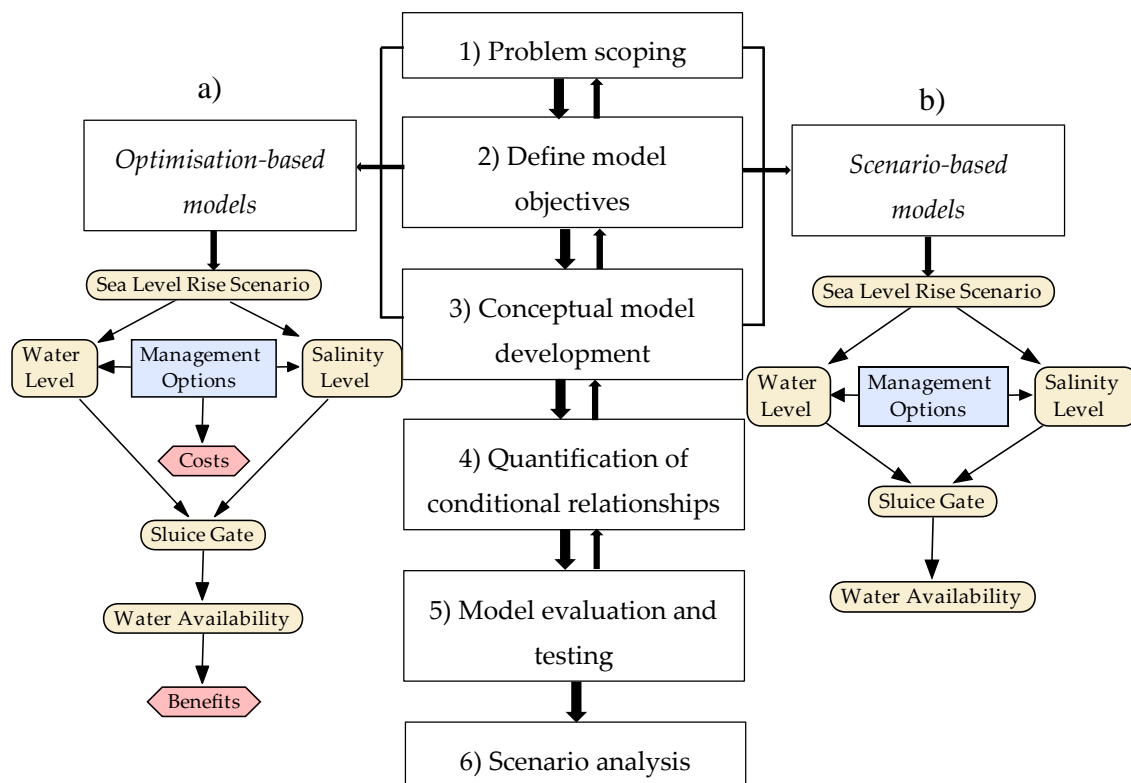


Figure 1. Main steps in developing a Bayesian network (BN) (adapted from Ames et al. [16], Bromley et al. [19], Ticehurst et al. [20]), and an example BN configured for: (a) Optimization-based decision support, featuring a decision node (coloured blue) with an associated cost node indicating the costs for implementing the different management options, and a benefit node indicating the desirability of the different states of water availability which result at the output node; (b) scenario-based decision support, featuring a decision node without the associated cost node, and an output node without an associated benefit node.

These different modelling approaches can be constructed using six iterative steps (Figure 1), to produce a valid and useful BN for decision-making support:

- (1) *Problem scoping*: Identify challenges confronting the management of water systems by collecting and analysing historical data on key drivers to understand problems in the systems under study.
- (2) *Define model objectives*: Identify the aim of the model (e.g., optimisation of appropriate management measures, or understanding relationships among key variables of the system) and select stakeholders to involve in the modelling process.

- (3) *Conceptual model development*: Identify the important system variables (including management measures and their attribute values) and their relationships in the system. Identification of this information may be based on a literature review, historical data analysis, and consultation with stakeholders.
- (4) *Quantification of conditional relationships*: Assign states and probabilities to each variable in the system using historical data, other modelling results, and elicitation from stakeholders.
- (5) *Model evaluation and testing*: The model can be evaluated and tested using quantitative methods (e.g., sensitivity analysis and assessments of predictive accuracy) and/or qualitative methods (e.g., feedback from experts).
- (6) *Scenario analysis*: BNs can be used as decision support tools because they allow an assessment of the probability of changes in the states of response or target nodes in the system, associated with management measures or scenarios contained in the model.

2. Methods

2.1. Systematic Quantitative Literature Review

An appraisal of BN applications for supporting decision-making in water resource management was conducted by undertaking a systematic quantitative review of relevant English language academic articles in three electronic databases (Web of Science, Scopus, and Google Scholar). Relevant articles (up to June 2019) were extracted from these databases by using a combination of ('BN model', 'Bayesian*', 'Bayesian belief networks', or 'Bayesian networks', or 'Bayesian decision networks', or 'BBNs', or 'BNs') and change related search terms ('water*', or 'water resources', or 'river'). The wildcard ('*') was used for Bayesian and Water to match all words around these two keywords. The title, abstracts and keywords of articles were included in these searches. Books or book chapters, review papers, conference proceedings and purely theoretical articles were not considered in this review.

The resulting database of academic research papers reporting on BN applications in decision-making supports for water resource management was then attributed according to the following fields: (a) The research aims of reviewed studies, (b) the types of data used in BN development for identifying adaptation options (quantitative or/and qualitative data), (c) consideration of climate change impacts (e.g., changes in sea level rise, precipitation and temperature) and socio-economic stressors (e.g., population growth and changes in agricultural and industrial production) on water resource management, (d) the basis for informing decision support (optimization-based or scenario-based), and (e) the types of adaptation measures considered (institutional and social measures; technological and engineered measures, and ecosystem-based measures).

The categorization of the types of adaptation options considered in the reviewed BN papers follows that used in the report of Intergovernmental Panel on Climate Change (IPCC) in 2014 [4]. This categorization is used here because climate change and socio-economic stressors are major drivers of the need for adaptation in the management of water resource systems worldwide. It is important to be clear that adaptation measures, as responses to stressor-induced changes, are distinct from any scenarios (e.g., population growth, sea-level rise) which might be applied to investigate the performance of those adaptation measures. The categories of adaptation options defined in the 2014 IPCC Report [4] are:

- (i) Institutional and social measures: i.e., the inclusion of economic and social instruments, laws, regulations, policies and educational programs (e.g., water prices, water rights, and awareness raising)
- (ii) Technological and engineered measures: i.e., the inclusion of technologies and methods (e.g., new crops, water-saving technology, irrigation efficiency technology), and constructions (e.g., desalination plants, wastewater treatment, reservoirs and rainwater tanks)
- (iii) Ecosystem-based measures: i.e., the inclusion of green infrastructure and ecosystem services (e.g., forest cover, riparian planting and restoration)

2.2. Statistical Analysis

Chi-square tests of independence were used to quantify whether there was a relationship between the types of data used, the types of management options considered and the decision-making approach of the BNs in the reviewed studies. The frequencies of each category of these variables were calculated for the analysis. Conducting the Chi-squared tests of independence for these variables aims to see the trend in the application of BNs as decision support tools for water resource management, under climate change and socio-economic development.

3. Results

A total of 819 relevant articles were initially identified from Scopus, Web of Science and Google Scholar after eliminating duplications. However, a perusal of the abstracts revealed that 686 of these articles did not specifically discuss the application of BNs to water resource management. The remaining shortlist of 133 articles was therefore examined in detail, to evaluate the application of BNs as decision-making support tools in water resource management (Table 1), to quantify the extent to which these applications used different data collection approaches to develop optimization- and scenario-based models, for the evaluation of different categories of management measures.

Table 1. List of reviewed applications of BNs as decision support tools for water resource management in the academic literature, published through to June 2019. *QT: Quantitative data, QL: Qualitative data, ISM: Institutional and social measures: TEM: Technological and engineered measures: EM: Ecosystem-based measures: NO: No management measure consideration SC: Scenario-based decision making approaches, OP: Optimization-based decision making approaches, PR: Predictive only.*

Research Aims	Data Usage	Management Measures	Decision Making	Reviewed Studies	
Water quality management	QL	EM	SC, OP	McVittie et al. [21]	
		NO	SC	Joseph et al. [22]	
			PR	Tang et al. [23], Cheng et al. [24]	
	QT	EM	SC	Lee et al. [25], Moe et al. [26]	
			SC, OP	Sadoddin et al. [27]	
		ISM	OP	Mesbah et al. [17]	
			SC	Nikoo et al. [28]	
		ISM, TEM, EM	SC	Forio et al. [29]	
		TEM	SC	Hines and Landis [30]	
		TEM, EM	SC, Op	Said [31]	
		NO	PR	SC	Ha and Stenstrom [32], Murray et al. [33], Nikoo et al. [34], Park and Stenstrom [35], Wang et al. [36], Liu et al. [37], Mayfield et al. [38], Wijesiri et al. [39]
					Dyer et al. [40], Liyanage and Yamada [41], McLaughlin and Reckhow [42], Nojavan et al. [43], Ramin et al. [44]
		Both	EM	SC, OP	Keshtkar et al. [45]
	SC			Lynam et al. [46]	
	ISM		SC	Bertone et al. [47]	
	ISM, EM		SC	Dorner et al. [48], Ticehurst et al. [49]	
			SC, OP	Rivers-Moore [1]	
	ISM, TEM		SC	Reckhow [50]	
	ISM, TEM, EM		SC	Carpani and Giupponi [51], Holzkaemper et al. [52]	
	TEM, EM		SC, OP	Kragt et al. [53]	
NO	SC	Hamilton et al. [54]			
	PR	Pollino et al. [14], Pike [55]			

Table 1. Cont.

Research Aims	Data Usage	Management Measures	Decision Making	Reviewed Studies
Groundwater management	QL	ISM, TEM	SC	Giordano et al. [56], Roozbahani et al. [57]
		TEM	SC	Aguilera et al. [58]
	QT	NO	PR	Fienen et al. [59], Nolan et al. [60], Shihab [61], Moghaddam et al. [62]
		ISM	SC	Carmona et al. [63], Carmona et al. [64], Henriksen et al. [65], Olalla et al. [66], Subagadis et al. [67]
	Both	ISM, EM	SC	Mohajerani et al. [68]
		ISM, TEM	OP	Farmani et al. [69]
			SC, OP	Molina et al. [70]
		NO	PR	Ghabayen et al. [71], Martín de Santa Olalla et al. [72]
Water supply management	QL	TEM	SC	Chan et al. [75]
		ISM	SC	Pang and Sun [76], Avilés et al. [77]
	QT	TEM	OP	Ahmadi et al. [78], Bullene et al. [79], Ghabayen et al. [80]
		NO	PR	Francis et al. [81], Hunter et al. [82], Peng et al. [83]
	Both	ISM	SC	Dondeynaz et al. [85], Fisher et al. [86]
			SC	Pagano et al. [87], Moglia et al. [88]
		TEM	SC, OP	Moglia et al. [89]
			ISM, TEM, EM	SC
Irrigation management	QL	TEM	SC	Barron et al. [93]
		ISM, TEM, EM	SC	Cain et al. [94]
	QT	NO	PR	Maleksaeidi et al. [95]
		ISM	SC	Andriyas and McKee [96]
		TEM, EM	SC	Robertson and Wang [97]
		NO	SC	Rahman et al. [98], Sherafatpour et al. [99]
	Both	ISM	SC	Quinn et al. [100], Wang et al. [101]
		ISM, TEM	SC	Mamitimin et al. [102]
TEM		OP	Batchelor and Cain [8]	
NO		PR	Castelletti and Soncini-Sessa [103], Saravanan [104]	
River related management	QT	EM	SC	Johns et al. [105]
		ISM, TEM, EM	SC, OP	Stewart-Koster et al. [106]
	SC, OP		Hjerppe et al. [107]	
	Both	NO	SC	Leigh et al. [108], Shenton et al. [109]
		EM	SC	Allan et al. [110], Morrison and Stone [111]
		TEM	SC	Calder et al. [112]
		TEM, EM	SC, OP	Borsuk et al. [113]
		ISM, EM	SC	Ropero et al. [114]
NO		PR	Chan et al. [115]	
		SC	Varis et al. [116]	

Table 1. Cont.

Research Aims	Data Usage	Management Measures	Decision Making	Reviewed Studies	
Nutrient management	QL	NO	PR	Tattari et al. [117]	
		ISM	SC	Alameddine et al. [118], Couture et al. [119]	
	QT	TEM	SC, OP	Ames et al. [16]	
		TEM, EM	SC	Death et al. [7]	
	Both	NO	PR	Qian and Miltner [120], Wijesiri et al. [121]	
		ISM	SC	Borsuk et al. [122], Borsuk et al. [123], Nash and Hannah [124]	
		ISM, TEM, EM	SC, OP	Barton et al. [6]	
		NO	SC	McDowell et al. [125], Sperotto et al. [126]	
Water supply and demand management	QT	ISM	SC, OP	Portoghese et al. [18]	
		ISM, TEM	SC	Sušnik et al. [127]	
	Both	NO	PR	Geraldi and Ghisi [129]	
		ISM	SC, OP	Molina et al. [130]	
		ISM, TEM, EM	SC	Xue et al. [3]	
		ISM, TEM	SC	Bromley et al. [19]	
	Reservoir management	QT	NO	SC	Said et al. [131], Varis and Kuikka [132]
			ISM	SC	Mediero et al. [133]
TEM			SC	Malekmohammadi et al. [134]	
Both		NO	SC	Ropero et al. [135]	
		ISM	PR	Kim et al. [136]	
		ISM, OP	PR	Landuyt et al. [137]	
Wastewater treatment management	Both	NO	PR	Chen et al. [138]	
Water demand management	Both	NO	PR	Cheon et al. [139], Li et al. [140]	
Water and energy management	Both	NO	PR	Inman et al. [141]	
Water and energy management	Both	ISM, TEM	SC, OP	Bertone et al. [142]	

3.1. Research Aims of the Reviewed Studies

Ten different categories of research aims in water-related management were considered in the reviewed studies (Table 1). Water quality management was the major concern addressed by reviewed studies (29%), followed by water supply management (16%), groundwater management (14%), nutrient management (8%) and irrigation management (8%). Water demand was less considered in the reviewed studies. Depending on the different research aims of these reviewed studies, the decision-making approaches and management measures were considered differently to achieve expected outcomes, and to adapt to climate change and/or socio-economic development. Scenario-based decision support was considered for almost all research aims. However, optimisation-based decision support was considered for only four research aims, including water quality management (e.g., [17]), groundwater management (e.g., [69]), water supply management (e.g., [80]) and irrigation management (e.g., [8]). In addition, a combined scenario-based and optimisation-based approach was considered frequently for river-related management (e.g., [113]), water supply and demand management (e.g., [18]) and nutrient management (e.g., [6]).

3.2. Type of Adaptation Options

A considerable number of these reviewed studies were designed with respect to climate change (e.g., changes in sea level, precipitation and temperature) and/or socio-economic stressors (e.g.,

population growth, changes in industrial and agricultural production). A wide range of management measure types were therefore considered to adapt to changes in climatic and/or non-climatic drivers (Table 1). The category of management measures was considered differently in different research aims. Institutional and social management measures were considered for almost all research aims. Technological and engineered measures were considered most frequently for management of water supply (e.g., [78,87]) and irrigation (e.g., [8,93]) while ecosystem-based measures were considered most frequently for management of river-related issues (e.g., [105,110]), water quality (e.g., [26,45]) and nutrients (e.g., [6,7]).

3.3. Use of Quantitative and Qualitative Data

Almost half of the reviewed studies (47%) applied both quantitative and qualitative data to construct DAGs and populate CPTs in their BNs (Figure 2a). Quantitative data was used by only 58 reviewed studies (44%), whereas very few studies (9%) developed networks using only qualitative information (Figure 2a).

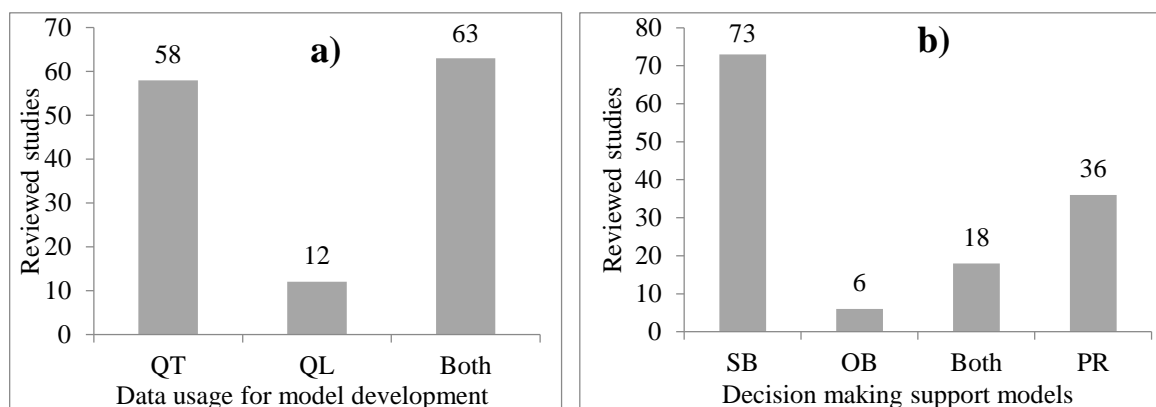


Figure 2. Usage of different types of data in BN construction (a) and usage of BNs for different types of decision support (b) in water resource management. QT: Quantitative data, QL: Qualitative data, Both: Both quantitative data and qualitative data, SB: Scenario-based approaches, OB: Optimization-based approaches, Both: Both scenario and optimization-based approaches, PR: Predictive only.

A chi-squared test of independence indicated that there was no significant difference in the use of quantitative and/or qualitative data across BNs used for optimization-based versus scenario-based decision support ($p = 0.544$). Neither was there any significant difference in the use of quantitative data and/or qualitative data in BNs used to evaluate the performance on the different categories of management measure ($p = 0.249$).

3.4. Decision Making Support Approaches and Evaluation of Management Options of the Reviewed Studies

The general value of BNs as decision support tools is evidenced by their widespread use in water resource management, with more than 72% of the reviewed studies reporting that their BNs were developed to support decision-making processes. About a quarter of the reviewed articles ($n = 36$), described BNs, which were developed for predictive modelling only (Figure 2b). The scenario-based approaches were most commonly used to evaluate the effectiveness of management options under different scenarios, accounting for 68% of the reviewed applications (Figure 2b). Optimization-based approaches were encountered much less frequently, only appearing in 18% of the reviewed applications. Only seven (e.g., [1,45,106]) of these optimization-based studies actually incorporated decision nodes, cost node(s) and utility node(s) into their BNs to optimize selection of water-related management options. Other studies (e.g., [17,18]) coupled BNs with external economic valuations to optimize the selection of water management measures.

A total of 76 reviewed studies (57%) evaluated the performance of management options for water resource systems. More than 61% of these seventy-six studies evaluated the performance of institutional and social management measure (ISM), while 47% considered technological and engineered measures and 37% evaluated ecosystem-based measures (Figure 3). More than 36% of these seventy-six reviewed applications considered management measures from more than one management category. For example, eight studies (11%) evaluated the performance of all three categories of management measure (ISM, TEM and EM), and nineteen studies (25%) in total evaluated two categories of measures for water resource management (Figure 3).

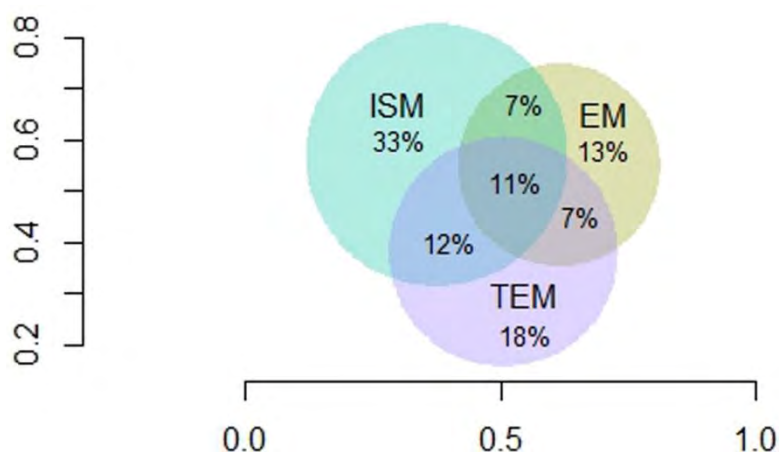


Figure 3. Evaluation of different categories of management measures in the reviewed studies. *ISM*: Institutional and social measures, *TEM*: Technological and engineered measures, *EM*: Ecosystem-based measures.

Scenario-based approaches were used frequently to evaluate every category, and category combination, of management measures (Figure 4). In contrast, optimization-based approaches were applied significantly less frequently to evaluate the performance of institutional and social measures. A chi-squared test of independence indicated that there was significant dependence ($p = 0.076$) between the types of management measure(s) being evaluated and the decision support approach used for that evaluation (optimization-based model versus scenario-based models versus combined optimization and scenario-based models).

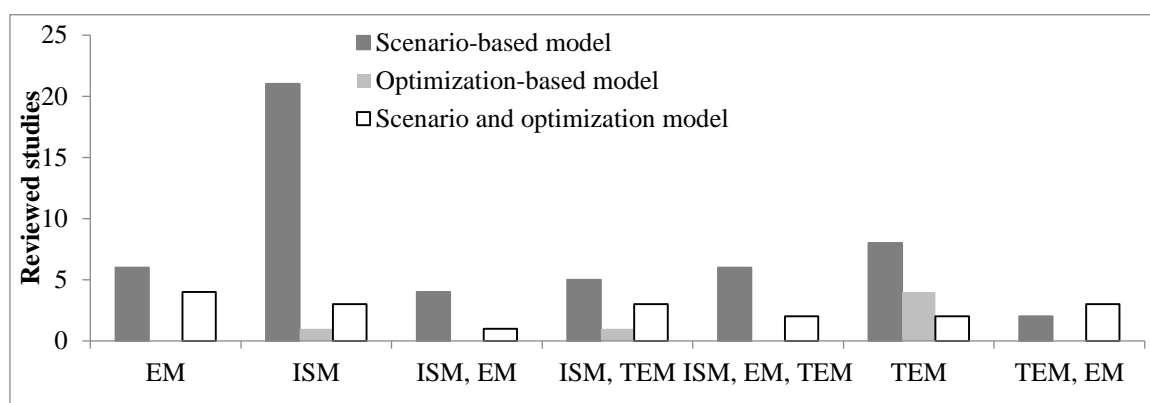


Figure 4. Application of optimization and scenario-based approaches to evaluate different categories of management measures. *ISM*: Institutional and social measures, *TEM*: Technological and engineered measures, *EM*: Ecosystem-based measures.

3.5. Discussion and Recommendations

This systematic quantitative literature review has found that a considerable number of studies have applied BNs as a decision support tool to evaluate the performance of management options to inform

decision-making for complex and uncertain systems, in relation to a wide variety of water-related issues. In particular, water quality management, water supply management, groundwater management and irrigation management are the major concerns on which the majority of BN applications have been focused on, to date. A high proportion of these studies have sought to understand climatic and/or non-climatic drivers and their impacts on water-related systems and to evaluate the performance of management options under these changing conditions. Effects of numerous climatic drivers have been considered, including sea-level rise on water supply management (e.g., [2]), and on water quality management (e.g., [49]); precipitation and temperature on groundwater management (e.g., [63,64,67]), on reservoir management (e.g., [135]), on water supply management (e.g., [3,132]), on water quality management (e.g., [27,43,45]) and on nutrient management (e.g., [119,126]) and precipitation on water supply and demand management (e.g., [18,127,130,131]). Similarly, the non-climatic drivers that have been considered, have included effects of population growth on water supply and demand management (e.g., [128]), and on water quality management (e.g., [41]); crop production changes in irrigation system management (e.g., [96,102]); population growth and agricultural production on water supply and demand management (e.g., [128]); agricultural production on irrigation water management (e.g., [93–95,100]), on water supply management [93,95,100], on water supply management (e.g., [85]), and on groundwater management (e.g., [67]); changes in domestic use and in agricultural and industrial production on water supplies and demand management (e.g., [127]).

Most BN applications identified in this review were found to use both quantitative and qualitative data for the model setup, parameterization and/or calibration. Different types of quantitative and qualitative data were collected in relation to the research aims and data availability of the reviewed studies. Empirical data and model simulations were the two main sources of quantitative data used to construct and calibrate BN applications. Empirical data include water quality samples (e.g., [58]), riparian vegetation and ecological measures (e.g., [106]), dam operation data and population (e.g., [128]), irrigated areas (e.g., [18]) and Geographic Information System (GIS) data (e.g., [81]). Model simulation data from different types of models included a system dynamics model (e.g., [16]), a two-dimensional habitat simulation model (e.g., [115]) and a groundwater flow model (e.g., [59]). Qualitative data (e.g., expert knowledge and stakeholder opinion) are frequently used to calibrate and validate the BNs where empirical data are lacking [15,21]. For example, expert knowledge was used to identify the environmental factors (e.g., land use, rainfall, storage level, agricultural areas) affecting the three key water quality parameters (turbidity, colour and crypto) in the reservoirs of New South Wales, Australia, and then quantify the relationships between environmental factors and these water quality variables through populating the CPTs for the model [47]. In addition, meetings with stakeholders, water managers, water experts and researchers were organized to determine the influential variables (e.g., water for people and animals, industrial water demand, groundwater exaction) and their relationships on a water supply and demand system, and then elicit the CPTs based on average values from all participants for the system in Qira Oasis area, Northwest China [3]. The ability of BNs to combine these different types of data is particularly useful for informing decisions under high levels of uncertainty, where the state of a variable or decision outcome is uncertain. This is because BNs are well suited to facilitate stakeholder involvement to identify potential intervention options and incorporate stakeholder expertise to assess the likely consequences of each option even where detailed quantitative data on outcomes is incomplete [1].

Bayesian networks have been widely used in the management of environmental systems with many motives, such as understanding the systems, predicting the current and future changes of the systems under different scenarios, evaluating the performance of management measures, conducting trade-off analysis for selecting an optimal management measure, and informing and supporting decision making with or without participatory process [143]. This systematic quantitative literature review quantified the reviewed studies, applied decision support approaches in the management of complex and uncertain systems, and found that most of these reviewed studies applied scenario-based approaches to help decision-makers or modellers understand water-related systems, and answer the

question ‘what if?’, through evaluating the effectiveness of management measures under exploring different scenarios (e.g., [51,127]). Optimization-based approaches were also applied but less frequently. The output of optimization-based approaches was designed to help decision-makers or modellers understand water-related systems and answer the question ‘what is best?’, through conducting trade-off analysis to find out the most optimal management options with/without exploring different scenarios (e.g., [17,137]). Only 27% of reviewed studies developed BNs for predictive modelling only, meaning that these studies just focused on understanding the systems without exploring any scenarios or management measures (e.g., [36,60,141]).

A major finding from this review is that there was no significant difference in the use of quantitative and/or qualitative data for both developing decision-making support models and evaluating different management measures. However, a significant dependence was found between the types of management measures being assessed and the decision support approaches used to evaluate the performance of those measures. This may be driven by implementation constraints, especially given the challenges inherent in quantifying the costs and benefits of institutional and social measures sufficiently for inclusion in the optimization-based approaches. It is also inherent that the nature of cost and utility functions will probably influence the decision of selecting optimal management measures derived from the optimization-based approaches, and thus, values of cost and utility should also be estimated as accurately as possible [106]. Another potential challenge of the optimization-based approaches is their performance assessments. Barton et al. [6] indicated that the modellers faced a particular challenge to validate the performance of optimisation-based approaches because they include cost and utility functions. In addition, sensitivity analysis is not able to be conducted to identify the influential levels between factors and targeted variables in the optimization-based approaches. Thus, these challenges may explain why cost-benefit and cost-effectiveness optimization approaches are only rarely applied to evaluate the performance of these types of measures.

A wide range of adaptation options, encompassing engineered and technological measures, institutional and social measures, and ecosystem-based measures can be incorporated into BNs to help decision-makers evaluate the effectiveness of these measures for water resource management. Potential outcomes from these measures can be described using qualitative and/or quantitative data. BNs have the capacity to help decision-makers consider multiple and potential interactions and interventions among adaptation options in water resource systems under climate change and socio-economic stressors. Institutional and social measures were found to be the most frequently assessed category of management measure. This may be because this category includes a wide range of measures, such as water pricing (e.g., [18,64,102,130]), compensation payments (e.g., [69]), discharge permits (e.g., [3,28]), educational programs (e.g., [2,67]) and improvements in management practices (e.g., [29,65,100,137]).

This review found that the performance of institutional and social management measures was more often evaluated by scenario-based approaches than by optimization-based approaches, whilst, the performance of technological and engineered measures was mainly evaluated by optimization-based approaches. It is likely to be much more straightforward to estimate implementation costs for engineered and technical measures, such as the construction of reservoirs (e.g., [3,29,31,134]), desalination plants (e.g., [70,79,89]), rainwater tanks (e.g., [2,88]) and improvements in irrigation technology (e.g., [102]), than to estimate the societal costs arising from institutional and social measures, such as modifications to property rights, community education programs or increasing household water prices. Depending on the system and adaptation measures being considered, the societal benefits delivered by institutional and social adaptation measures could be estimated by methods such as author expertise (e.g., [21,106]), market valuations and literature reviews (e.g., [8,16]), non-market valuation (e.g., [6]) and interviews with local experts (e.g., [137]).

Another important finding is that a combination of scenario-based and optimization-based approach was more often applied to evaluate ecosystem-based management measures, such as riparian planting and restoration options (e.g., [7,45,53]) or increasing forest cover (e.g., [26,94]). The use of optimization-based approaches to assess the performance of ecosystem-based measures has been

suggested, but it is possible that the inclusion of ecosystem-based measures in BNs may be inhibited by a lack of comparable standards and methodologies for assessing their effectiveness [4]. Therefore, both scenario-based and optimization-based approaches were applied to evaluate the performance of ecosystem-based measures under different potential scenarios as a way of identifying robust management options. The successful evaluation of ecosystem-based management methods again illustrates the usefulness of the ability for a BN to incorporate expert opinion to bridge knowledge gaps where precise data are lacking [15].

Institutional and social measures might be capable of providing highly cost-effective or cost-efficient solutions, but results from the review suggest that they are less likely to be evaluated in optimization-based decision support. We propose two potential solutions to this dilemma. Firstly, interdisciplinary collaborations are to be encouraged because they can combine engineering and technical expertise to determine potential outcomes from institutional and social measures with economics and social science expertise, to quantify the societal costs and benefits of implementing measures as diverse as reallocating property rights or increasing household water prices. Secondly, multi-criteria decision analysis (MCDA) should be considered as a possible optimization approach because of its ability to answer ‘which is best?’ questions, where data for the cost of implementation is lacking. When using MCDA, it is typically sufficient to know that all proposed management options are deemed feasible and acceptable from societal and technical perspectives, by the group of stakeholders involved in BN construction and decision support. A ‘which is best?’ analysis can then be conducted based on multiple outcomes, weighted appropriately by agreed preference weightings from decision-makers. BNs could contribute very effectively to MCDA, in which the heuristic possibilities of BNs could be extremely useful. An approach combining MCDA and BNs could enable these to complement each other to support the decision-making process further. For example, in a system safety assessment, Fenton and Neil [144] applied BNs to compute values for each criterion with uncertainty for a given action, and then MCDA was applied to combine the values and rank the actions. The authors indicated that BNs might not provide a complete solution for the safety assessment system with multiple criteria (e.g., economic, environmental and political criteria) and, in this case, MCDA is needed to weight these criteria to make an appropriate decision on the nature of deployment. In addition, Khakzad and Reniers [145] applied both BNs and MCDA in the risk-based design of chemical plants. More specifically, BNs were employed to estimate both on-site and off-site risks posed by potential major accidents in chemical plants. The results of BNs were used as input data in MCDA to find an optimal layout for chemical plants. The authors stated that BNs facilitated the incorporation of complicated interdependencies and conditional probabilities encountered in accident analysis and risk assessment, and that MCDA allowed considering incommensurate and conflicting decision parameters, inevitable in most decision analyses.

Although BNs have considerable potential for decision-making support in water resource management under climate change and socioeconomic stressors, they also have some limitations in their development and calibration [6,13,103]. In this review, two main limitations were discussed based on evidence from the reviewed studies. The first potential limitation in these types of applications is knowledge bias in expert elicitation for both scenarios and management interventions. Although experts can have considerable knowledge of water resource systems, the challenges inherent in integrating this knowledge into complex water system models may affect model outcomes [13]. In addition, time commitment and dominant personalities are potential challenges to the process of constructing BNs using expert-derived data [146]. For example, a study by McVittie et al. [21] used qualitative data alone to assess and value the delivery of ecosystem services from riparian buffer strips. The authors voiced concern that although BNs are a promising participatory decision support tool, trade-offs between realism, precision and the benefits of stakeholder involvement in the decision-making process have to be considered carefully before embarking on their use. Chen and Pollino [143] also stated that BNs can be built entirely from expert elicitation or data learning;

however, models may be more meaningful and valuable when expert elicited prior probabilities, and then empirical data, updated the models.

Another challenge for the application of BNs as decision support tools for water resource management concerns their quantitative calibration and validation. Empirical data (e.g., field observations) or independent assessments are needed to increase confidence in the ability of BNs to identify appropriate management strategies [6,15]. For example, Death et al. [7] collected invertebrate communities and GIS data from Manawatu River, New Zealand, to develop BNs for an invertebrate-based measure of ecological conditions under different management scenarios. The authors indicate that using empirical data for calibration and validation of BNs could enhance model performance, and lead to more confident decision making. In addition, Hamilton et al. [54] used water quality monitoring data, simulation models and expert opinion to develop BNs for exploring the major factors influencing algal blooms in Deception Bay, Queensland, Australia. The authors suggest that the use of observation data for calibrating BNs may lead to more robust results. Thus, to promote the performance of BNs for water resource management, decision-making will require a greater emphasis on the use of empirical data to construct and refine models, and/or to validate expert opinions.

Although BNs have been applied widely in these settings, several recommendations can be made on the basis of this review for future research priorities and challenges, which should be considered to further develop BNs as decision support tools for managing water resource systems under climate change and socio-economic stressors:

- (1) Where possible, empirical data should be used to construct and validate BNs to increase model performance and assist in identifying robust adaptation options.
- (2) Model parameterization and the estimation of the costs and benefits of all the different categories of management options in BNs for decision support should be based on interdisciplinary collaborations and a range of different sources, including expert opinions, market and non-market valuations and modelling results.
- (3) Ecosystem-based measures have been applied less frequently in BN decision support models, but these types of measure could offer win-win solutions for both water resource management and ecosystem service delivery.
- (4) Bayesian networks could be configured to deliver multi-criteria decision analysis to facilitate 'which is best?' decision support, where cost data for particular management option types are not available.

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