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Special Series

Dynamic Bayesian Networks to Assess Anthropogenic and Climatic Drivers of Saltwater Intrusion: A Decision Support Tool Toward Improved Management

Grace Rachid,† Ibrahim Alameddine,† Majdi Abou Najm,‡ Song Qian,§ and Mutasem El-Fadel†*

†Department of Civil & Environmental Engineering, American University of Beirut, Beirut, Lebanon
‡Department of Land, Air and Water Resources, University of California at Davis, Davis, California, USA
§Department of Environmental Sciences, The University of Toledo, Toledo, Ohio, USA

EDITOR'S NOTE:

This article is part of the special series "Applications of Bayesian Networks for Environmental Risk Assessment and Management" and was generated from a session on the use of Bayesian networks (BNs) in environmental modeling and assessment in 1 of 3 recent conferences: SETAC North America 2018 (Sacramento, CA, USA), SETAC Europe 2019 (Helsinki, Finland), and European Geosciences Union 2019 (Vienna, Austria). The 3 sessions aimed at showing the state-of-the-art and new directions in the use of BN models in environmental assessment, and focusing on ecotoxicology and water quality modeling. This series aims at reflecting the broad applicability of BN methodology in environmental assessment across a range of ecosystem types and scales, and discusses the relevance for environmental management.

ABSTRACT

Saltwater intrusion (SWI) is a global coastal problem caused by aquifer overpumping, land-use change, and climate change impacts. Given the complex pathways that lead to SWI, coastal urban areas with poorly monitored aquifers are in need of probabilistic-based decision support tools that can assist in better understanding and predicting SWI, while exploring effective means for sustainable aquifer management. In this study, we develop a Bayesian Belief Network (BBN) to account for the complex interactions of climatic and anthropogenic processes leading to SWI, while relating the severity of SWI to associated socioeconomic impacts and possible adaptation strategies. The BBN is further expanded into a Dynamic Bayesian Network (DBN) to assess the temporal progression of SWI and account for the compounding uncertainties over time. The proposed DBN is then tested at a pilot coastal aquifer underlying a highly urbanized water-stressed metropolitan area along the Eastern Mediterranean coastline (Beirut, Lebanon). The results show that the future impacts of climate change are largely secondary when compared to the persistent water deficits. While both supply and demand management could halt the progression of salinity, the potential for reducing or reversing SWI is not evident. The indirect socioeconomic burden associated with aquifer salinity was observed to improve, albeit heterogeneously, with the application of various adaptation strategies; however, this was at a cost associated with the implementation and operation of these strategies. The proposed DBN acts as an effective decision support tool that can promote sustainable aquifer management in coastal regions through its robust representation of the main drivers of SWI and linking them to expected socioeconomic burdens and management options. *Integr Environ Assess Manag* 2021;17:202–220. © 2020 SETAC

Keywords: Bayesian network Saltwater intrusion Aquifer management Adaptation Decision models

INTRODUCTION AND BACKGROUND

Saltwater Intrusion (SWI) has been reported in various coastal zones around the world such as New Zealand (EnviroLink 2011), China (Zhang et al. 2011), Philippines (Sales 2009), Korea (Park et al. 2012), US (Conrads et al. 2010; Sanford and Pope 2010), Bangladesh (Rahman et al. 2014), and India (Bobba 2002). The Mediterranean basin is no exception, with SWI reported along its northern, southern, and Eastern sections (e.g., France [De Montety et al. 2008], Italy [Capaccioni et al. 2005], Spain [Fatoric and Chelleri 2012], Turkey [Cobaner et al. 2012], Syria [Allow 2012; Abou Zakhem and Katta 2017], Lebanon [Rachid et al. 2017; Saadeh and Wakim 2017; Zaarour 2017], Israel [Levi et al. 2018; Mushtaha et al. 2019], Gaza [Selmi 2013], Egypt [Attwa et al. 2016; Eissa et al. 2016], Tunisia [Kouzana et al. 2009], Libya [El Hassadi 2008] and Morocco [El Yaouti et al. 2009]).

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* Address correspondence to ia04@aub.edu.lb

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Complex coastal aquifer hydrodynamics and the uncertainties associated with future climate change limit our abilities to quantify and predict SWI (Sanford and Pope 2010; Werner et al. 2013). Moreover, interactions between global climate change and local environmental drivers (e.g., urbanization with land use and land cover) remain poorly characterized. As such, the ability of coastal cities to manage and adapt to SWI is constrained by the complexity of the process, the limited data availability, and the associated high uncertainties (Tribbia and Moser 2008). In this context, Bayesian networks (BNs) can be an attractive decision support tool for risk analysis and management (Barton et al. 2008; Fenton and Neil 2012; Gonzalez-Redin et al. 2016; Li et al. 2018; Marcot and Penman 2019). The BNs are models that use the probability theory to quantify relations between variables and calculate outcomes (Pearl 1988; Marcot 2012). The BNs link variables (each with a set of states and prior probabilities) in a directed acyclic graph and calculate posterior probabilities of outcome states, while propagating the associated uncertainties. They are effective in accommodating incomplete data, accounting for uncertainty, and integrating knowledge-based and expert-based information (Aguilera et al. 2011; Eurie Forio et al. 2015; Marcot and Penman 2019). The BNs also allow for forward and backward propagation of information. This allows new information to be easily incorporated in the model as soon as it is made available. The BNs are also attractive as decision support tools given their legible graphical interface that is user-friendly for the nontechnical users (Fenton and Neil 2012; Fienen et al. 2013; Molina et al. 2013; Gonzalez-Redin et al. 2016). Additionally, BNs can be built as Bayesian decision networks through incorporating decision variables and the associated utility values. Traditionally, BNs have been run as standalone models that are static with respect to time. Recent developments have expanded the capabilities of traditional BNs, coupling networks together to generate Object-Oriented Bayesian Networks, which allow complex domains to be described in terms of interrelated subnetworks (Gine-Garriga et al. 2018). Further, time slicing has permitted the development of Dynamic Bayesian Networks (DBNs) for temporal analysis and predictions of future states (Molina et al. 2013).

Given these advantages, Bayesian decision networks have been successfully used to manage surface water resources, water contamination, and groundwater abstraction as well as to model catchments and irrigation needs (Ames et al. 2005; Sadoddin et al. 2005; de Santa Olalla et al. 2007; Molina et al. 2010; Fienen et al. 2013; Keshtar et al. 2013; Moe et al. 2016). The BNs in the environmental realm were also used in risk assessments, hazard analysis, ecological modeling, natural resources management, water quality assessment, and water and/or groundwater management in addition to conflict resolution (Borsuk et al. 2004; Bromley et al. 2005; Newton 2009; Alameddine et al. 2011; Giordano et al. 2013; Wu et al. 2016). However, their application in climate change related studies and adaptation management remains limited (Hall and Twyman 2005; Cuddy et al. 2007; Catenacci and Giupponi 2013; Couture et al. 2018) and their use toward assessing saltwater intrusion is lacking. In this study, a conceptual DBN framework is developed and presented as an environmental management tool with applicability to semiarid coastal areas affected by SWI with the aim of improving our understanding about the interaction between local anthropogenic drivers and global climatic determinants responsible for SWI in data-scarce and poorly monitored urbanized coastal aquifers. Additionally, we assess the socioeconomic implications of SWI that are associated with the projected changes in the physical environment and/or in the implementation of different policy drivers, while ensuring that the associated uncertainties in the data are accounted for and propagated transparently. The DBN is then used to compare between a set of proposed demand and supply management scenarios by assessing their abilities towards limiting and/or reversing SWI under projected climatic changes and sociodemographic transformations.

MATERIAL AND METHODS

Study area

The study area consists of the highly urbanized metropolitan area (Beirut, Lebanon) located on a relatively flat triangular-shaped peninsula extending westward into the Mediterranean Sea (Figure 1). It has a surface area of 40 km^2 with a 5-km shoreline and diverse features including rocky shores, sandy beaches, and cliffs. Topographically, the study area starts at sea level, then gains elevation along the Southwest and Northeast directions to reach a maximum of 95 m asl (Abdel Basit 1971). Its population is nearly 1.2 million (CDR/DAR 2014) residing in about 18 000 buildings (MoE/UNDP 2011) at a density of around 20 167 person/Km^2 (Ayash 2010). The population growth has been reported to range from 0.4 to 2.5% per year (El Fadel et al. 2000; CAS 2008; MOEW 2010; WB 2010). The study area has witnessed rapid urbanization, at a 111% increase between 1963 and 2005 (Faour and Mhawej 2014). With increased urbanization, the natural terrain of the study area was converted rapidly to impermeable surfaces (ESCWA 2005). The annual rainfall in the city ranges from 700 to 900 mm/y (Atlas Climatique du Liban 1977; Peltekian 1980; El-Samra et al. 2016) with an average annual temperature of 20.9 °C (Atlas Climatique du Liban 1977; tu.tiempo 2016). Climatic predictions point toward a drier and warmer future as well as to a rising sea level at a rate of 20 mm/y, which may reach up to 30–60 cm by 2040 (MoE 2011; MoE/UNDP/GEF 2016).

The underlying geology of the study area belongs to the Cretaceous and Quaternary periods with pockets of the Tertiary periods (Figure 1). Groundwater occurs mainly in 2 principal aquifers of sand and carbonate (Abdel Basit 1971). Available water resources to the city consist mainly of the water supplied through the public water network from nearby basins and groundwater wells

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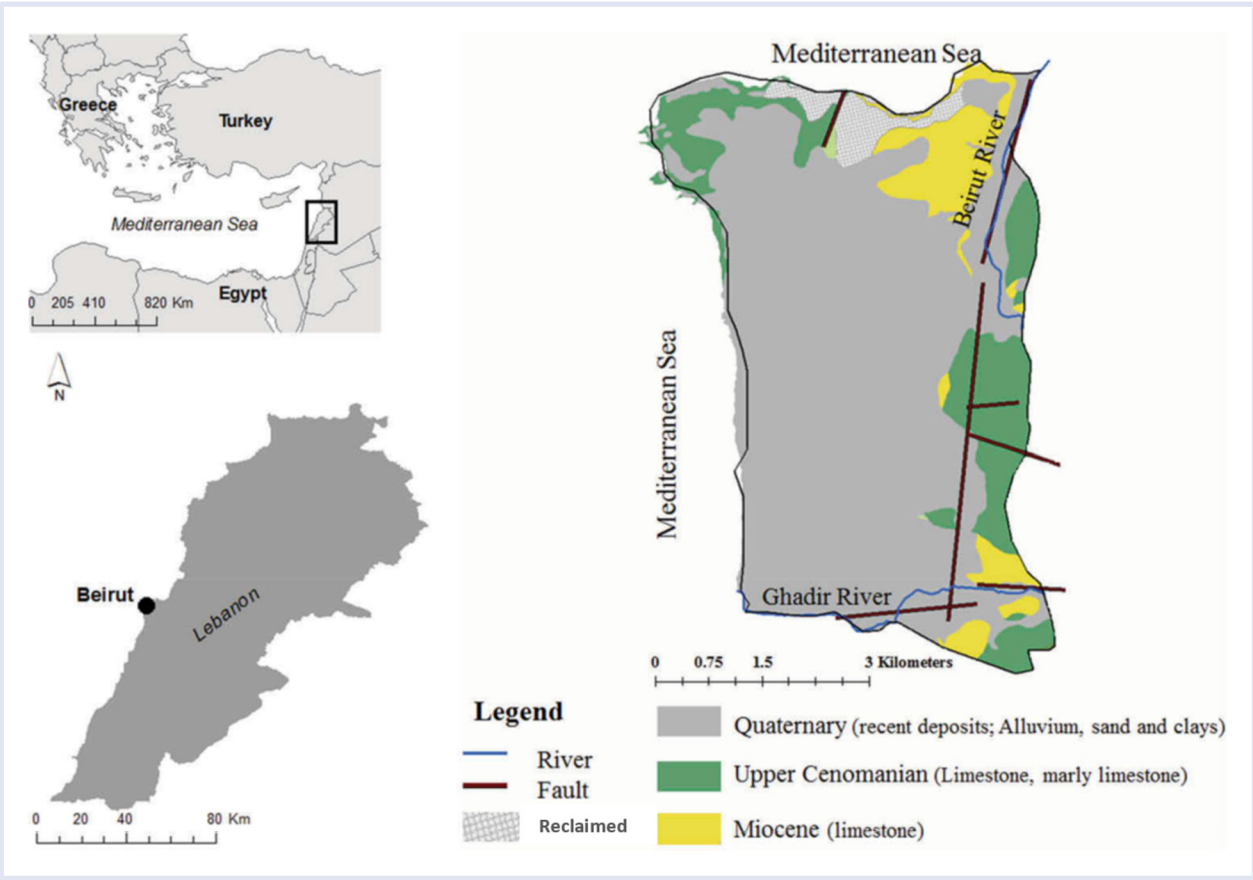

Figure 1. Location and geology of the study area.

(Acra et al. 1997; El Fadel et al. 2000; Saadeh 2008; Nasr et al. 2012). The daily supplied volume is estimated at 183 000 and 283 000 m^3/d for the summer and winter seasons, respectively; while the demand is estimated to exceed 303 000 m^3/d (Saadeh 2008). As a result of this deficit, the residents rely heavily on tapping into subsurface aquifers to fulfill their unmet water needs (Acra et al. 1997; Ayash 2010). According to CAS (2008), out of the 18 000 buildings in Beirut at least 5000 operate a private well with a total yield of more than 14 MCM (million cubic meters) per year (Peltekian 1980; Saadeh 2008; MOEW 2010; MoE/UNDP 2011).

The SWI along the Beirut coastal aquifer

Signs of SWI in Beirut were observed as early as 1969, through geoelectrical processing that confirmed SWI through tectonic fractures (FAO 1997). Since then, Cl^- concentrations steadily rose from 340 mg/L in 1970 to over 4200 mg/L in 1985 (Khair 1992). In a more recent study, Rachid et al. (2017) analyzed 170 wells between 2012 and 2014 and reported that the aquifer suffers from advanced salinity (average Cl^- concentration = 4600 mg/L) albeit with significant spatial and temporal heterogeneity. While these high levels of Cl^- are mostly driven by increased water demand and groundwater overextraction (abstraction beyond the recharge capacity of the aquifer), they are expected to further intensify in the future under the synergy of climate change impacts and population growth.

Conceptual model development and parameterization

Anthropogenic and climatic drivers will influence the propensity of SWI in coastal aquifers. Studies have generally focused on three main drivers, namely groundwater abstraction, aquifer recharge, and sea level rise (SLR) (Harbor 1994; Purandara et al. 2010; El Shinnawy and Abayazid 2011; Cobaner et al. 2012; Sophiya and Syed 2013; Safi et al. 2018). Population growth and increased urbanization are the main anthropogenic inducers of SWI, as they increase water demand and reduce natural groundwater recharge (Cobaner et al. 2012; Koussis et al. 2012; Selmi 2013). In addition, the daily water consumption rate plays an important role in determining the total water demand for a given area. The rate is known to differ geographically, temporally, and as a function of affluence (Whitcomb 2005). When the supply is short of the demand, groundwater extraction and SWI increase, especially when monitoring and enforcement are weak.

Climate change is another driver of SWI through multiple routes including the reduction in precipitation, the increase in ambient temperature and evapotranspiration, and the rise of sea level (Javadi et al. 2012; Sherif et al. 2012). A decrease in precipitation is expected to reduce the recharge

and negatively affect available freshwater resources. On the other hand, an increase in ambient temperature is associated with a greater water demand (Goodchild 2007; Jarboo and Al-Najar 2015) and evapotranspiration (Bates et al. 2008; Jackson et al. 2011; Neukum and Azzam 2012). The rise in sea level is expected to imbalance the saline-freshwater hydrostatic pressure and enhance the lateral seawater intrusion (Reilly and Goodman 1985; Conrads et al. 2010; Chang et al. 2011; Carretero et al. 2013; Werner et al. 2013). While the general trends governing the physical, geological, and chemical interactions between these drivers and the intensity of SWI are common, the direction and magnitude of these interactions are highly context-specific (Loáiciga et al. 2011; Ferguson and Gleeson 2012; Ivkovic et al. 2012).

As groundwater salinity levels increase, it becomes unusable for most purposes. Hence, salinization is associated with an economic burden in terms of incurring "avoidance costs" such as tapping into alternative resources, purchase of water, or the treatment of the salinized water to acceptable levels prior to use (Characklis et al. 2005; Connor et al. 2012; Catenacci and Giupponi 2013). Moreover, consuming high salinity waters shortens the useful lives of piping systems, fixtures, and appliances (water heaters, coolers, faucets, clothes washers, and dishwashers) and damages the infrastructure. These in turn result in increased expenditures on maintenance and repairs (Ragan et al. 2000; Wilson 2004; Howitt et al. 2009; Connor et al. 2012; Alameddine et al. 2018). Additionally, the consumption of high salinity water has been associated with adverse health impacts (Frank and Boyer 2014; Talukder et al. 2016; Ur Rahman et al. 2017). Overall, the scale of these damages is expected to intensify in view of the synergies between the seemingly inevitable impacts of climate change and the ever-increasing human-induced pressures (Nicholls et al. 2007).

For the study area, the available literature, exploratory data analysis, and experts' knowledge were used to formulate a conceptual framework for SWI (Kragt 2009; Giordano et al. 2013; Keshtkar et al. 2013; Phan et al. 2016). Figure 2 depicts the framework of SWI along coastal aquifers representing the drivers, their effects or impacts, their potential interactions, and their implications.

Transforming the conceptual framework into a BN model requires the identification of variables representing the parent and child nodes as well as establishing the conditional relationships between them (Kragt 2009; Catenacci et al. 2013; Keshtar et al. 2013; Phan et al. 2016). Starting with the conceptual framework (Figure 2), the structure and variables of the SWI Directed Acyclic Graph (DAG) were developed in an iterative process involving reviews and feedback from domain experts. While most nodes in the conceptual framework were directly represented as variables in the SWI DAG (e.g., temperature, rainfall, population growth rate, consumption rate, aquifer salinity, freshwater recharge), others were captured by a set of variables (e.g., avoidance costs, lateral flow).

The final SWI DAG (Figure 3) consisted of multiple variables categorized into 4 components, namely a climate component, a hydrogeological component, a demographic component, and a socioeconomic component. The climate component accounts for the current conditions of temperature, rainfall, and evapotranspiration, as

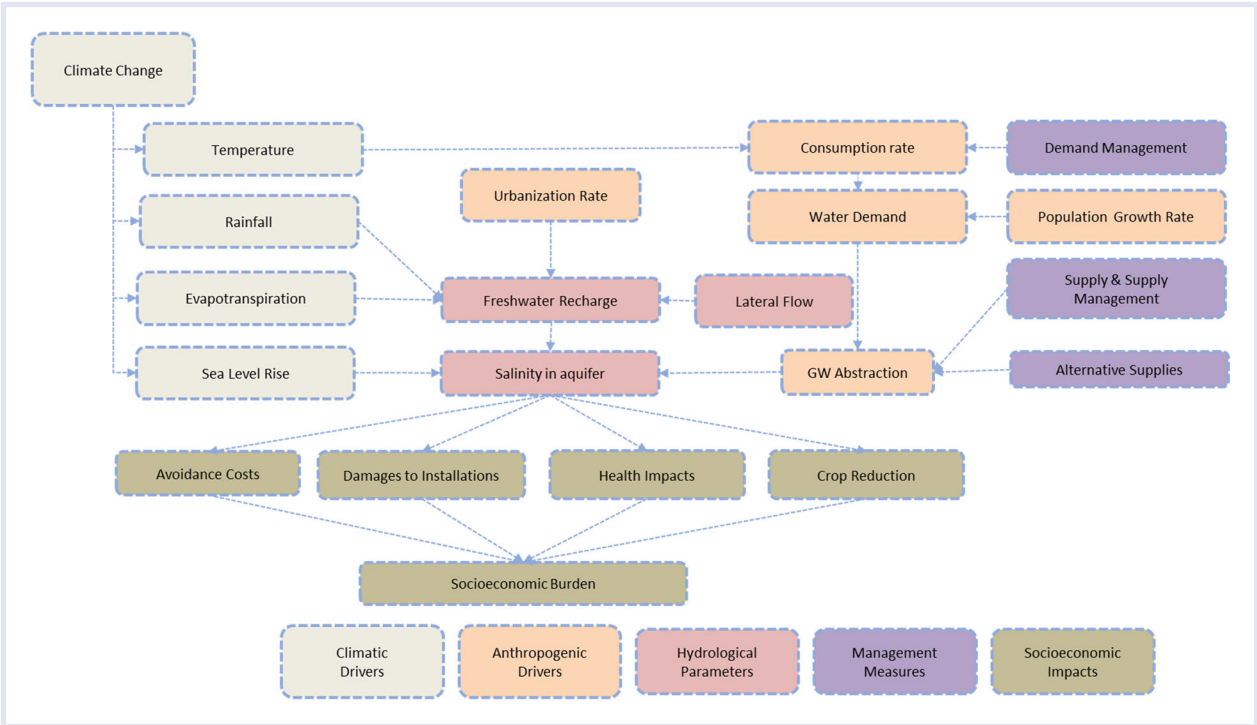

Figure 2. Conceptual framework for the main drivers of saltwater intrusion and their impacts.

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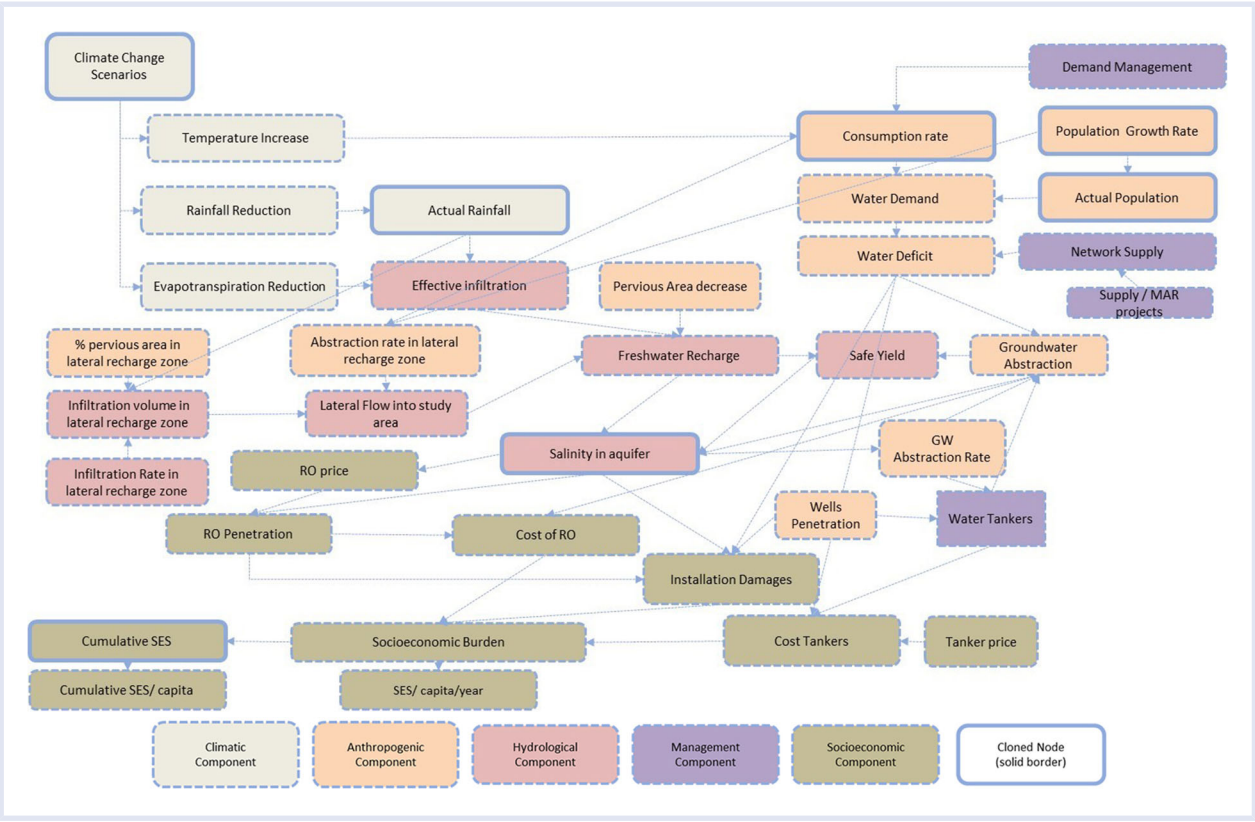

Figure 3. Proposed directed acyclic graph for the Saltwater Intrusion Dynamic Bayesian Network. Cloned node: are select variables that represent the interface between 2 successive time slices in the DBN allowing for the modeling of time series.

well as their projected future changes as defined by the RCP 4.5 and RCP 8.5 scenarios (IPCC 2014). Note that while the impact of SLR on aquifer salinity was initially included as a node in the conceptual framework, it was omitted due to the inconclusive nature in the direction and intensity of the relationship between SLR and salinity (Reilly and Goodman 1985; Chang et al. 2011; Carretero et al. 2013; Werner et al. 2013). The main route by which SLR affects salinity is through the advancement of the freshwater-seawater mixing zone and the interface toe, the dynamics of which can only be described through a spatially distributed numerical model specific for the aquifer. In this context, Safi et al. (2018) reported that the impact of SLR on salinity levels was negligible when compared to the magnitude of existing anthropogenic drivers. The demographic component of the model relates the current population and its potential growth over time along with the water consumption rates to estimate water demands. The hydrogeological component was divided into 2 subcomponents, namely lateral flow and salinity. The lateral flow subcomponent characterizes the recharge area outside the aquifer domain that contributes freshwater into the study area. It links the infiltration, pervious area, and abstraction rates in the mountainous recharge area, overlooking the city to the net freshwater recharge inflowing into the study area. Thus, it represents the total lateral flow. On the other hand, the salinity subcomponent defines the relationships governing how the drivers of SWI (freshwater recharge, rainfall infiltration, pervious area, abstraction, and safe yield) affect the salinity levels of the aquifer. Finally, the socioeconomic component relates the resulting salinity levels to the direct and indirect costs incurred by the targeted population as a function of avoidance costs that included the cost of treatment (e.g., reverse osmosis), damages to installations, or costs of using alternative sources (i.e., trucking water).

As the DBN is intended to be used as a decision support tool, a management component was included to explore the implications of potential or planned mitigation measures and adaptation strategies (i.e., demand and supply management options). Figure 3 illustrates the resulting DAG including the nodes and links associated with the multiple model components. Full details on the model set up and its components are presented in the online Supplemental Data.

The definition of the states for each node was based on reported literature, field surveys, and stakeholders' elicitation (Table 1) (Keshtkar et al. 2013; Phan et al. 2016; Sperotto et al. 2017). The number of states was kept as low as possible to account for the need to populate the conditional probability tables (CPTs) (Table 1) (Chen and Pollino 2012; Eurie Forio et al. 2015). As some nodes are

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Table 1. Nodes, states, and parametrization of the saltwater intrusion Dynamic Bayesian Network

Component	Node Name[a]	Unit[a]	States	Parameterization
Climatic	CC scenarios (P) (C)	RCP	4.5; 8.5	Output from global circulation models
	Temperature increase	°C/y	$0–2.5\times10^{-3}$; 2.5×10^{-3} –0.0208; 0.0208–0.037	Output from dynamic downscaling model (WRF[a] HiRAM[a] model)[b,c]
	Actual rainfall (C)	mm/y	<350; 350–550; 550–750; 750–950; 950–1100	Literature & data[b,c]
	Rainfall reduction	%/y	0.006–0.01; 0.01–0.015; 0.015–0.02	Output from dynamic downscaling model (WRF HiRAM model)[b,c]
	Evapotranspiration reduction	%/y	$0–4.97\times10^{-4}$; 4.97×10^{-4} – 9.91×10^{-4}; 9.91×10^{-4} – 3.85×10^{-4}	Output from PRECIS model[c,n]
Hydrogeological lateral flow	% pervious area in the lateral recharge zone (P)	%	1–10; 10–30; 30–50	Data & literature[d]
	Infiltration volume in the lateral recharge zone	MCM/y	0–1; 1–2; 2–3	Equation*
	Infiltration rate in the lateral recharge zone (P)	%/y	10–20; 20–30; 30–60	Expert interviews
	Abstraction in the lateral recharge zone	MCM/y	0–0.6; 0.6–1.6	Equation*
	Lateral flow into the study area	MCM/y	0–1; 1–2; 2–3	Equation* – mass balance
Demographic	Population growth rate (P) (C)	%/y	0.2–1.2; 1.2–2.2; 2.2–3.2	Data & literature[e]
	Actual population (C)	Million	1–1.2; 1.2–1.4; 1–1.6; 1.6–2.2	Data & literature[f]
	Consumption rate (C)	l/c/d	<70; 70–100; 100–200; 200–300	Equation*
				Data & literature[g]
	Water demand	MCM/y	<10; 10–50; 50–100; 100–150; 150–250	Equation*
	Water deficit	MCM/y	0–1; 1–5; 5–10; 10–40; 40–140; 140–220	Equation*
Hydrogeological salinity	Effective infiltration in study area	MCM/y	0–0.2; 0.2–0.4; 0.4–0.6	Equation* [Eq. 1]
	Pervious area decrease (P)	%/y	0–0.2; 0.2–0.5; 0.5–1	Expert elicitation Literature[d,h]
	Freshwater recharge	MCM/y	0–0.5; 0.5–2.5; 2.5–4.5; 4.5–8	Equation*
	Network supply	MCM/y	30–50; 50–110; 110–180; 180–240	Official data[i]
	Groundwater abstraction	MCM/y	0–1; 1–5; 5–10; 10–40; 40–140; 140–250	Equation*

(*Continued*)

Table 1. (*Continued*)

Component	Node Name[a]	Unit[a]	States	Parameterization
	Safe yield	MCM/y	0–1; 1–5; 5–10; 10–40; 40–140; 140–250	Equation*
	Groundwater abstraction rate (function of aquifer salinity)	% of previous year	10–50; 50–60; 60–75; 75–100	Expert elicitation
	Salinity in aquifer (C)	ppm	1000–4000; 4000–7000; 7000–10000; 10000–15 000; 15 000–25 000; 25 000–35 000	Equation* – Mass balance [Eq. 2]
Socioeconomic	RO penetration	% of buildings	0–5; 5–10; 10–20; 20–40	Field survey + expert elicitation
	RO price	$/m^3	0–0.3; 0.3–0.5; 0.5–1; 1–2	Expert interviews
	RO cost (at the city level)	MUS$/y	0–0.8; 0.8–10; 10–320	Equation*
	Installation damages (at the city level)	MUS$/y	0–1; 1–2.5; 2.5–5	Equation* – Regression Model [Eq. 3]
	Water tankers (market penetration)	% of buildings	5–25; 25–35; 35–55; 55–80	Field survey
	Tanker price (price of water delivered by tankers)	$/m^3	3–8; 8–12	Literature[j]
	Cost of tankers (annual cost of delivery at the city level)	MUS$/y	0–5; 5–10; 10–60; 60–200; 200–900	Equation*
	Annual socioeconomic (SES) burden (at the city level)	MUS$/y	0–5; 5–10; 10–50; 50–100; 100–500; 500–1000; 1000–2400	Equation*
	Cumulative SES burden (C)	MUS$	0–5; 5–2000; 2000–3000; 3000–4800; 4800–7000; 7000–10 000; 10 000–24 000	Equation*
	Cumulative SES (over project life) per capita	$/capita	0–250; 250–500; 500–1500; 1500–2500; 2500–5000; 5000–10 000; 10 000–24 000	Equation*
Management	GBWSP Phase I	MCM/y	0–30–60	Official data[k]
	GBWSP Phase II	MCM/y	0–30–60	Official data[k]

(*Continued*)

Table 1. (*Continued*)

Component	Node Name[a]	Unit[a]	States	Parameterization
	Desalination	MCM/y	0–60–120	Literature[l]
	Artificial recharge	MCM/y	0–3.5	Official data[k]
	Demand Management (P) (increase in tariff)	%	0–50; 50–150; 150–300	Data & literature[m]

* Equations detailed in Supplemental Data II.
[a] (P) parent node; (C) temporal clone node; (RCP) Representative Concentration Pathways; (MUS$) million US dollars; (MCM) million cubic meters; (GBWSP) Greater Beirut Water Supply Project; (WRF) Weather Research and Forecasting model; (HiRAM) High Resolution Atmospheric Model.
[b] El-Samra et al. 2016.
[c] Atlas Climatique du Liban 1977, SNC 2011, TNC 2016.
[d] Faour and Mhawej 2014.
[e] CAS 2008, WB 2009, MOEW 2010, El Fadel et al. 2000.
[f] CDR/DAR 2014, Ayash 2010, MoE/UNDP 2011.
[g] WB 2009, MoE/UNDP 2011, MOEW 2010, Comair 2010, Saadeh 2008, Peltikian 1980, El-Fadel et al. 2000.
[h] El-Fadel et al. 2015.
[i] MOEW 2010, Saadeh 2008, MoE/UNDP 2011.
[j] Constantine et al. 2017.
[k] MOEW 2010, WB 2017.
[l] Saidy 2016.
[m] MOEW 2010.
[n] PRECIS Model, Met Office Hadley Center (2010).

continuous, we implemented discretization to convert these variables into a set of finite bins that will act as the node states. Discretization is often a required step when implementing BNs, since most inference algorithms can only use categorical data. Based on Fienen et al. (2013), natural thresholds evident from the physical environment were used first in addition to meaningful ranges reported in the literature. This was followed with an iterative process of fine-tuning the discretization process to ensure the generation of meaningful bins that are able to provide insights on the data and reflect changes. For example, the discretization of aquifer salinity followed the groundwater quality categorization into slightly, moderately, highly, and very highly saline based on the 6 salinity bins of Konikow and Reilly (1999). From this starting point, the bins were further refined whereby the extreme bins were compressed while the middle bins were expanded in order to provide a reasonable set of bins that can capture salinity changes (Table 1). While the selection of the discretization method can have potential impacts on the accuracy and computational efficacy of the model (Uusitalo 2007; Aguilera et al. 2011; Alameddine et al. 2011; Nojavan et al. 2014; Rahman et al. 2014; Lucena-Moya et al. 2015), the evaluation of the impact of the discretization method, albeit recognized, was kept out of scope of this study and should be examined in future work on this BN model. Populating the prior probabilities of the parent nodes as well as the subsequent CPTs was based on available data, reported literature, official statistics, field surveys, outputs from other models, expert elicitation, and interviews (Table 1) (Cain 2001; Nyberg et al. 2006; Pollino et al. 2007; Kjaerulff and Madsen 2008; Kragt et al. 2009; Chen and Pollino 2012; Catenacci et al. 2013; Nojovan et al. 2014; Rahman et al. 2014). For example, the probabilities for the nodes on RO price, RO penetration rate, well penetration rate, and the water tanker prices were populated based on field surveys (El-Fadel et al. 2015; Constantine et al. 2017) and expert interviews. Elicitation was undertaken through the direct fixed value elicitation approach (Morgan and Henrion 1990; Clemen 1991; Winkler 2003; Kashuba 2010). Additionally, a set of CPTs were populated based on functions representing mass balances and regression equations (Table 1). Note that the time span of the DBN was defined between 2014 and 2034, with a time step of 1 y. The baseline year was set at 2014. Table 1 summarizes the developed DBN by highlighting the type of nodes used, their states, and the basis for the parameterization of their CPTs. The HUGIN EXPERT 8.8 was used to build and run this DBN (HUGIN EXPERT 2019). Full information on the model parameters including the definition of the nodes' states and parameterization of CPTs are provided in the online Supplemental Data.

Dynamic Bayesian network

While a BN is an effective decision support tool, it is limited in its capacities to propagate information through time. As such, the BN model was further developed into a DBN. The latter has been applied in various fields including

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clinical (Orphanou et al. 2014; Zandona et al. 2019) and environmental studies (Molina et al. 2013; Uusitalo et al. 2018). The DBNs allow for the modeling of time series by generating a BN for each time slice and allowing the realization of selected variables at a given time to be dependent on the state of the system at past times, while maintaining the same DAG and node relationships throughout the time slices (HUGIN EXPERT 2019; Marcot and Penman 2019). These select variables are known as temporal clones that represent the interface between 2 successive time slices in the model (HUGIN EXPERT 2019). As such, simulations of the BN at any time slice will result in updates to the probabilities of states for all nodes including the clone nodes at that time slice. These clone nodes will then communicate their updated states to their clone in the next time slice so that the BN of the next time slice will estimate the updated probabilities of all nodes accounting for the carried input from the previous time slice. In this study, 7 out of 37 nodes were designated as clone nodes (refer to Table 1). In total, the DBN had 20-time steps (time step = 1 y) starting with the base year of 2014 and ending in 2034.

Model sensitivity analysis and evaluation

The model's sensitivity and performance were evaluated quantitatively and qualitatively. In terms of model sensitivity, both the sensitivity to findings, which measures how the posterior probability distributions (PPD) change under different conditions, and the sensitivity to parameters, which measures how PPD change when input variables are modified, were implemented (Pollino et al. 2007; Chen and Pollino 2012; Moe et al. 2016; Radl et al. 2018). Sensitivity to findings was quantified through the calculation of the value of information (VOI) (Pollino et al. 2007; Marcot 2012; Radl et al. 2018). The VOI identifies the variables with the highest mutual information with respect to a selected target node. The VOI ranges between 0 and 1, with lower values associated with mutually independent variables and higher values associated with more informative variables (Pollino et al. 2007). The VOI analysis was implemented on the 2 main model endpoints, namely aquifer salinity and socioeconomic burden for year 1 of the model run. Calculating it for future times was not possible due to time-slicing. Meanwhile, sensitivity to parameters (also known as influence analysis) was evaluated by: 1) quantifying changes in the PPDs of the target nodes when the parent nodes are altered (Pollino et al. 2007; Marcot 2012; Nojovan et al. 2014); and 2) computing the posterior probability certainty index (PPCI) proposed by Marcot (2012). The 1-sample Kolmogorov-Smirnov (KS) nonparametric test was used to determine if introducing evidence in 1 of the parent nodes resulted in a statistically significant change in the PPD of the target nodes (at $t = 1$ and for $t = 20$) as compared to the normative case (Marcot 2012). The PPCI was used to evaluate the uncertainty of the model outcomes through indexing the degree of dispersion of posterior probability values among outcome states after normalization with the number of states and possible minimum and maximum values (Marcot 2012). The PPCI values range between 0 and 1; higher values suggest greater certainty in outcome predictions. The PPCI values were calculated for the normative scenario as well as for model runs where input variables were modified. The PPCI were tracked over the 20-y time slices of the DBN for both aquifer salinity and socioeconomic burden target nodes.

Regarding model validation, it was largely qualitative and conducted through expert model walkthrough to review the representation of the model and assess its predictions in response to evidence initiation. We also attempted to validate the model by comparing its results to those from a 3D variable-density flow and solute transport model developed by Safi et al. (2018) for the same aquifer to determine the level of agreement in salinity predictions under a set of common scenarios. Finally, we conducted an assessment of the internal consistency of the target nodes through determining the area under the curve (AUC) based on the generation of 10 000 cases with the enforcement of a 10% missing completely at random (MCAR) rule.

Model simulations

The DBN was used to assess the relative importance of the projected changes in climatic forcing versus those associated with anthropogenic drivers on SWI through a set of scenarios (Table 2) by comparing their marginal probabilities on the target nodes (i.e., the salinity of the aquifer and the ultimate socioeconomic burden). A baseline scenario (S1) was defined under RCP 4.5 to represent the most probable situation in the study area. The impact of climatic variability was assessed in scenario (S2) under RCP 8.5. The worst case scenario (S3) coupled RCP 8.5 with a higher consumption rate of 200–300 l/c/d (instead of 100–200 l/c/d). Note that for all 3 scenarios, no changes were considered to the existing demand and supply management.

Several supply management scenarios were then defined and run under RCP 4.5 and 8.5 (Table 2). Based on governmental plans (MOEW 2010), S1-Sa and S3-Sa use 60 MCM of additional water by 2019 and scenarios S1-Sb and S3-Sb use an additional 60 MCM starting in 2025. In an effort to capture the urgency of implementing the proposed governmental supply projects, 2 scenarios (S1-Sc and S3-Sc) were proposed to capture the impact of delaying project execution. These scenarios assumed that the 120 MCM additional supply volume will only be made available for use starting from 2025 onward. On the other hand, scenario S1-MAR was defined to quantify the potential of Managed Aquifer Recharge (MAR) to limit the salinity in the aquifer by examining the impact of injecting ~3.5 MCM/year of freshwater (MOEW/UNDP 2014) into the Beirut aquifer under RCP 4.5. Finally, the impact of implementing demand management (S1-D and S3-D) was tested under both the most probable (S1) and the worst

Table 2. Scenarios assessed including driver variabilities and management decisions

Scenario	Scenario definition		RCP	Consumption rate l/c/d	Population growth rate %	Municipal supply projects
No management scenarios						
S1	Most probable		4.5	100–200	1.2–2.2	0
S2	Worsening climatic conditions		8.5	100–200	1.2–2.2	0
S3	Worst case		8.5	200–300	2.2–3.2	0
Management scenarios						
Supply management		Year[a]				
S1-Sa	Most probable	2019	4.5	100–200	1.2–2.2	60 MCM
S1-Sb		2019	4.5	100–200	1.2–2.2	60 MCM (2019)
		2025				+60 MCM (2025)
S1-Sc		2025	4.5	100–200	1.2–2.2	120 MCM
S3-Sa	Worst case	2019	8.5	200–300	2.2–3.2	60 MCM
S3-Sb		2019	8.5	200–300	2.2–3.2	60 MCM (2019)
		2025				+60 MCM (2025)
S3-Sc		2025	8.5	200–300	2.2–3.2	120 MCM
S1-MAR	Most probable + MAR of 3.5 MCM/y	2025	4.5	100–200	1.2–2.2	0
Demand management						
S1-Da	Most probable + Demand Management (150% tariff increase)	2019	4.5	100–200 (rate at base year)	1.2–2.2	0
S1-Db		2025				
S3-Da	Worst case + Demand Management (150% tariff increase)	2019	8.5	200–300 (rate at base year)	2.2–3.2	0
S3-Db		2025				

RCP = Representative Concentration Pathways; MAR = managed aquifer recharge; MCM = million cubic meters.
Year[a]: indicates the year at which the MAR, Demand Management, or Supply Management projects will be initiated.

case (S3) scenarios by introducing a 150% increase in the water tariff.

RESULTS

Climatic forcing and anthropogenic drivers under the no-action scenarios

Simulation of the most probable scenario (S1) showed that while in the base year (2014) there was a 99% probability that the aquifer's average salinity is in the slightly to moderately saline category (1000–7000 ppm), the probability that the average salinity level by the end year (2034) will exceed the 10 000 ppm level exceeded 90%. This reflects a significant increase in the average salinity of the aquifer (Figure 4). Under RCP 8.5 climatic forcing (S2), the probability that the average salinity of the aquifer in 2034 will exceed 10 000 ppm (highly saline) increased to 96%, with a 75% chance that the salinity will even exceed the 15 000 ppm (very highly saline). On the other hand, the results from the worst case scenario (S3) showed that the probability that by 2034 the aquifer's salinity will exceed the 10 000 or 15 000 ppm was 99% and 89%, respectively (Figure 4).

Naturally, this projected increase in aquifer salinity was associated with an increase in the socioeconomic burden on the community. The model projected that the burden per year will not exceed US$2500/capita/year (around 18% of the current average annual income per capita in Lebanon, estimated at $14 000 (MOF/UNDP 2017)) at any given year over the whole simulation period and across all scenarios (Figure 4). Under S1, it was projected with 53% probability that the burden is <$250/capita/year (around 2% of the current average annual income per capita) at the end year 2034 (initially 70% probability at the start year 2019) as compared to a 44% probability that the burden in 2034 is $500 to $1500/capita/year (around 3.5 and 10% of the current average annual income per capita) under S3. In parallel, the model projected a probability of 94% that the cumulative cost burden from avoidance costs and damages to installations (over 20 y) will exceed $1500 per capita which represents about double the cost per capita at the end year of the implementation of mega supply projects, estimated at a $820/capita. The probability that the cumulative costs will

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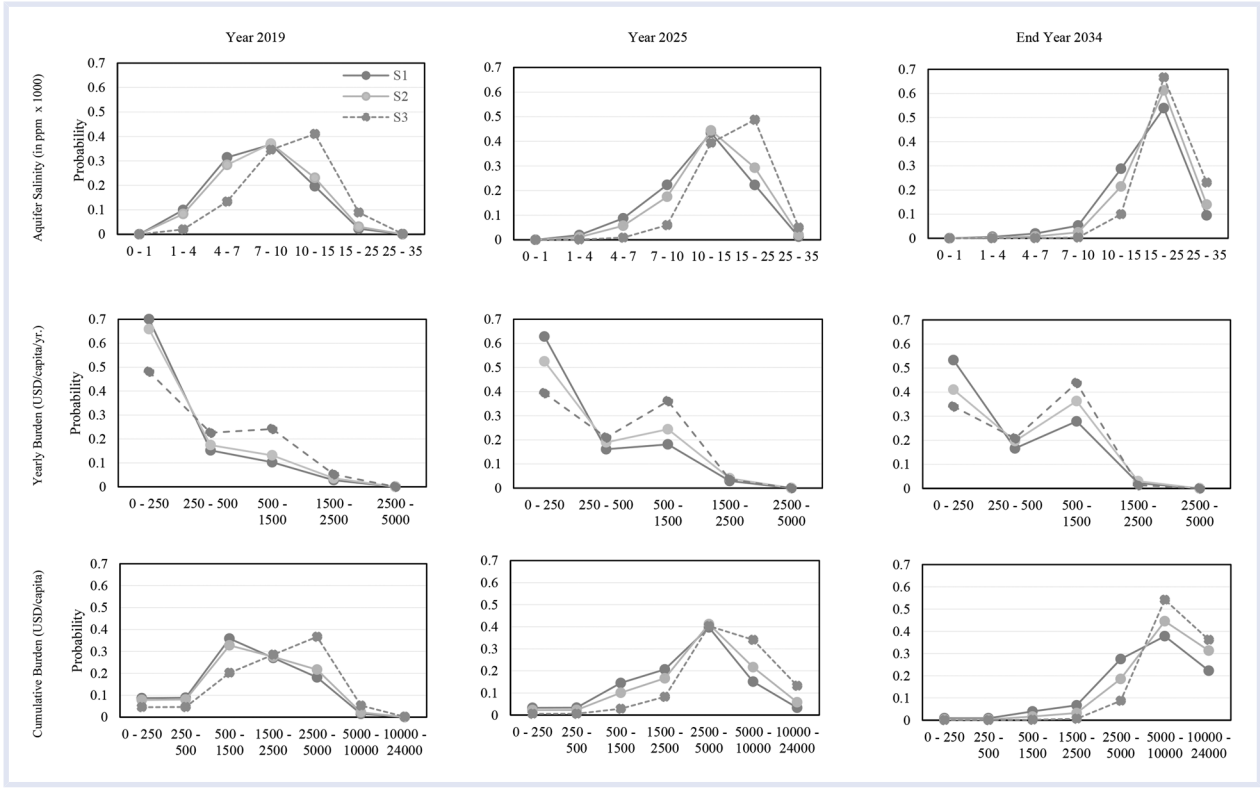

Figure 4. Probability of aquifer salinity (in ppm x1000) and socioeconomic burden (yearly in US$ per capita/y and cumulative in US$/capita) under S1: Most probable; S2: Climatic forcing; S3: Worst case scenarios. Posterior probability certainty index (PPCI) per scenario over time is illustrated in the Supplemental Data.

exceed $5000 per capita (around 35% of the current average annual income per capita) was 60% under S1 (Figure 4). The drastic increase in aquifer salinity projected under the worst case scenario (S3) was also associated with an equally sharp increase in the cumulative socioeconomic burden on the community projected at a 90% probability to exceed the $5000 per capita (around 6 times the estimated implementation cost of mega water supply projects at $820 per capita at end year) (Figure 4). Under the conditions defined for S2, this probability was estimated at 76% (Figure 4).

Projections with water management options

Managed aquifer recharge under the most probable conditions. Under the S1-MAR defined scenario, MAR exhibited little effect on reducing the probability that the aquifer salinity will exceed the 10 000 or 15 000 ppm marks by 2034. The drop in probability reached 8% and 4%, respectively, as compared to the probabilities estimated under S1 (Figure 5). Moreover, MAR did not reduce the socioeconomic burden significantly (Figure 6). The effectiveness of MAR may improve under greater availability of recharge volumes albeit the karst nature of the aquifer remains a challenge.

Supply management scenarios. The S1-Sa simulations (Figure 5) show that the supply of an additional 60 MCM starting 2019 can reduce the probability that the aquifer salinity will exceed the 15 000 ppm (very highly saline) in 2034 from 63% (under S1) down to 32%. This also translates into a significant decrease in the associated socioeconomic burden. The probability that the cumulative socioeconomic burden will exceed the $5000 per capita dropped from 60% under S1 to 25% under S1-Sa (Figure 6). Yet, this improvement comes with a significant investment cost (capital, maintenance, and operation) adding a financial burden on the community equivalent to ~$430 per capita (where the end year's (2034) population is estimated at 1 600 000 under the most probable scenario for the calculation of cumulative cost per capita). Increasing the supply under the S1-Sb scenario reduced the probability that the aquifer's salinity will exceed the 15 000 ppm level from 63% under S1 down to 15% (Figure 5). Similarly, this reduction in salinity translates into a reduction in associated socioeconomic burdens, whereby the probability that the cumulative burden by the end of the simulation period (i.e., by 2034) will exceed $5000 per capita was reduced to 8% as compared to 60% under S1 (Figure 6). Nevertheless, these benefits come at the cost of implementing such mega projects, which has been estimated at a cumulative cost of around $820 per capita. This scenario seems to be very promising in terms of delaying the deterioration of the aquifer and alleviating the socioeconomic burden. Comparing the actual cost of supply projects with the observed decrease in the projected salinity levels and the societal relief from salinity-induced burdens highlights the cost effectiveness and worthiness of this

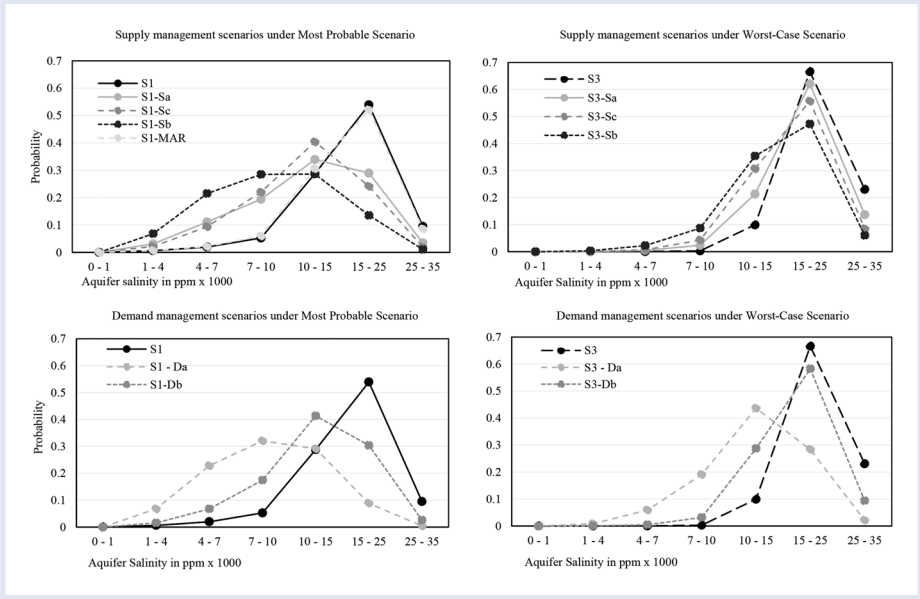

Figure 5. Probability of aquifer salinity (in ppm x1000) at end year (2034) under base cases, MAR, and demand and supply management scenarios; S1: Most probable; S2: Climatic forcing; S3: Worst case; Sa: 60 MCM supplied in 2019; Sb: 60 MCM supplied in 2019 and additional 60 MCM supplied in 2025; Sc: 120 MCM supplied in 2025; MAR: Managed Aquifer Recharge in 2025; Da: demand management starts in 2019; Db: demand management starts in 2025. Posterior probability certainty index (PPCI) per scenario over time is illustrated in the Supplemental Data.

project. The provision of additional water supply to reduce groundwater abstraction contributes also to the protection of the aquifer with ecological benefits.

Under worst-case conditions of climate and demand, supplying 60 MCM starting in 2019 (S3-Sa) can reduce the probability that salinity will exceed the 15 000 ppm (very highly saline) by 15% as compared to the worst case scenario (S3) without management actions. This improvement translates into a 21% reduction in the probability that the cumulative socioeconomic burden will exceed $5000 per capita (Figure 6). Under S3-Sb (Figure 5), the estimated probability that the average aquifer salinity in 2034 will exceed 15 000 ppm was 53%, which represents a 40% reduction in probability as compared to the no-action scenario under worst-case conditions (S3). The associated socioeconomic burden was also reduced, whereby the

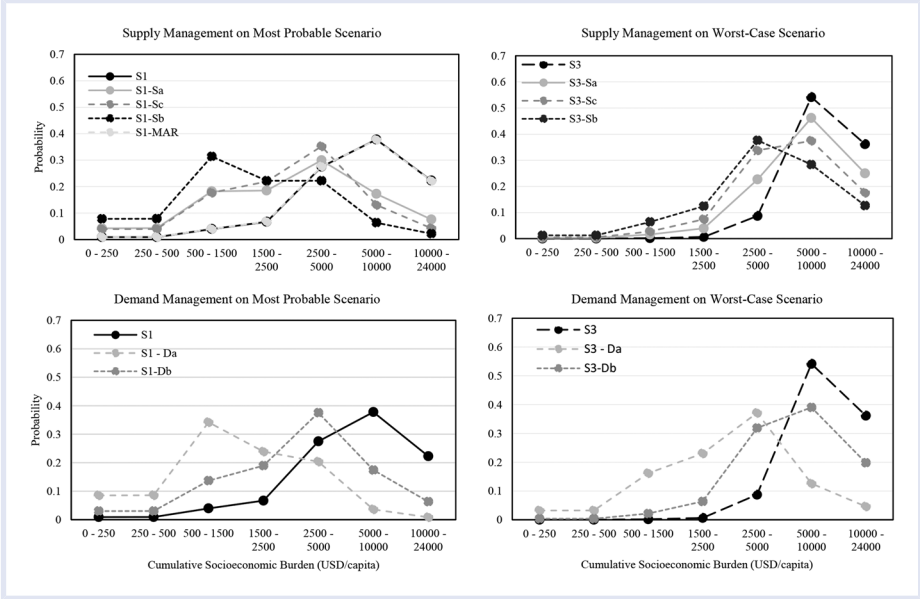

Figure 6. Probabilities of the cumulative socioeconomic burden (in US$ per capita) at end year (2034) under MAR, demand and supply management scenarios; S1: Most probable; S3: Worst case; Sa: 60 MCM supplied in 2019; Sb: 60 MCM supplied in 2019 and additional 60 MCM supplied in 2025; Sc: 120 MCM supplied in 2025; MAR: Managed Aquifer Recharge in 2025; Da: demand management starts in 2019; Db: demand management starts in 2025. Posterior probability certainty index (PPCI) per scenario over time is illustrated in the Supplemental Data.

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probability that the cumulative burden per capita by the end of the simulation period will exceed $5000 was around 40% as compared to 90% under S3 (a decrease of 55%) (Figure 6). These benefits, however, come with a high investment in supply projects, which translate into a cumulative cost per capita of $650 by 2034.

Demand management scenarios. Simulation of the impact of demand management in terms of increasing the water tariff by 150% under the conditions defined under the most probable scenario (S1) showed an 85% reduction in the probability that the average aquifer salinity exceeds 15 000 ppm as compared to S1 (Figure 5). The projected reductions in salinities minimized the socioeconomic burden significantly (Figure 6). Even under worst-case conditions of climatic change and population increase, the increase in tariff resulted in a 66% reduction in the probability that the average aquifer salinity will exceed 15 000 ppm by 2034 as compared to S3 (Figure 5). Additionally, the probability that the cumulative cost burden (over 20 years) will exceed $5000 per capita by 2034 was projected to decrease by 80% as compared to S3 (Figure 6).

Value of time. The value of time was examined by delaying the implementation of supply and demand management projects by 5 years under the S1 (most probable) and S3 (worst case) scenarios. For the supply management scenarios, the S1-Sc scenario (supply of 120 MCM starting 2025) showed an increase in the aquifer salinity as compared to scenario S1-Sb (supply of 60 MCM starting 2019, additional 60 MCM starting 2025) (Figure 5). As for the cumulative socioeconomic burden, it was estimated to exceed $5000 per capita, at the end year, by a probability of 17% as compared to the 60% probability projected under S1 and 8.5% under S1-Sb (Figure 6). These results reconfirm the benefits of an earlier intervention (Year 2019) and highlight the costs associated with these delays (Year 2025). Similar trends were observed under the worst-case conditions. The results from the S3-Sc scenario reflected a 17% increase in the probability that the aquifer salinity will exceed 15 000 ppm (very highly saline) by 2034 as compared to the S3-Sb scenario (Figure 5). On the other hand, the delay in project execution increased the probability that the cumulative socioeconomic burden by 2034 will exceed the $5000 per capita mark from 40% under S3-Sb to 51% (Figure 6).

Delaying the implementation of demand management by 5 y under the most probable scenario (S1-Db) increased the probability that the aquifer average salinity levels will exceed 15 000 ppm (very highly saline) from 38% under S1-Da to 74% (Figure 5). The delay also eroded the reductions in the socioeconomic burden. The probability that the cumulative socioeconomic burden per capita will not exceed the $5000 mark dropped from 96% if the project is initiated in 2019 to 76% if enforcement was delayed to 2025 (Figure 6). The delay of demand management under the worst-case conditions (S3-Db) resulted in even more significant losses. The probability that the salinity levels will exceed 15 000 ppm (very highly saline) by 2034 reached 67% as compared to the 30.5% if the tariffs were reformed starting in early 2019. Additionally, the probability that the cumulative cost burden (over 20 y) will exceed $5000 per capita by 2034 decreased by 34% as compared to S3, while the reduction reached 80% when the project was initiated in 2019.

DISCUSSION

The DBN clearly emphasized the high risk that the aquifer will become unusable within the next 20 y under the worst case scenario (increased water consumption coupled with population growth). The findings of the model showed that the impact of future climate change was largely secondary as compared to the chronic water deficits in the study area. Even under the favorable conditions of RCP 4.5, the aquifer was predicted to experience continued salinity increases if no management interventions are implemented. The major pathway through which the climatic drivers affected salinity was through increasing the water consumption rate as a result of higher temperatures. The relative impact of the predicted reductions in precipitation was comparatively low, given the low infiltration potential in the study area. In terms of the effectiveness of the considered management measures, the DBN results clearly showed that MAR was not an effective mitigation measure for the aquifer under study. Meanwhile both supply and demand management interventions proved effective in reducing the increase of salinity levels with time; yet their potential for reversing SWI was not evident. Still, demand management, through increasing the tariff rate to induce a reduction in the water consumption in order to reduce the demand on water, proved more effective in reducing salinities as compared to supply projects. However, the caveat with demand management is that it might nudge to adopt alternative sources (either recommended alternatives like greywater reuse and rainwater harvesting, or potentially problematic alternatives like unlicensed water tankers, unsafe water sources, and illegal wells). With regard to the indirect socioeconomic burden, the model results indicated that in the absence of management interventions they tended to increase over time. By the year 2034, the probability that the yearly socioeconomic burden per capita will exceed $500/capita/year (around 4% of the current average annual income per capita) ranged between 30 and 45%, depending on the defined scenarios. Moreover, the implementation of the defined management interventions proved to be effective in reducing or stabilizing this burden.

Regarding the sensitivity of the model, the results of the VOI (refer to Supplemental Data V-2) showed that groundwater abstraction, safe yield, and RO price were the most influential variables on the aquifer salinity target node. These 3 nodes accounted for 92% of the overall sensitivity in the aquifer salinity node. Regarding the socioeconomic burden node, the 5 top variables with highest mutual information (cost tankers, water deficit, groundwater abstraction, safe yield, and water demand) were able to account for around 78% of the observed sensitivity of the

node. The PPCI results (refer to Supplemental Data V-4 and V-5) showed greater certainty in the predictions of aquifer salinity as compared to those of the socioeconomic burden across the entire time frame. Moreover, the development of prediction certainty over the defined time frame differed between these 2 end nodes. While the PPCI of salinity largely had a parabolic shape, with higher outcome uncertainties occurring at intermediate times, the PPCIs of the socioeconomic burden target node tended to increase over time, with the exception of the high consumption rate scenario, where uncertainty slightly increased over time. Overall, the highest outcome certainty for future predictions (at year 2034) for both end nodes was under the worst case scenario. Meanwhile, the highest outcome uncertainty for both target nodes occurred under the normative scenario. Concerning the sensitivity of the target nodes to changes in the states of their parent nodes, the results of the KS analysis showed that both salinity and socioeconomic burden showed low sensitivity to changes in the climatic scenario both for year 1 and year 20 (refer to Supplemental Data V-3). Meanwhile, changes in demand management tended to have a significant impact on the PPDs of both target nodes both at year 1 and year 20. Regarding the anthropogenic forcings, only changes in the water consumption rate had an impact on the PPDs of both target nodes.

The experts' review provided positive feedback on the developed model. Meanwhile, the results of the AUC (refer to Supplemental Data V-1) returned AUCs > 0.7 for all nodes with the majority of nodes with an AUC > 0.9 with the exception of the nodes for % pervious area, infiltration rate of the lateral recharge zone, and pervious area decrease. Those 3 nodes had an AUC of 0.58 to 0.65. These AUC values suggest a good internal consistency of the model. Moreover, the salinity predictions of the developed DBN were found to be consistent with those from the mechanistic 3D variable-density flow and solute transport model (Safi et al. 2018). Both models running compatible scenarios were aligned in the direction and the relative impact of the investigated anthropogenic and climatic factors, showing that while the aquifer system is sensitive to both water consumption rates and population growth rates, coupling of both has a synergistic effect. Similarly, the 2 models underscored that while the proposed adaptation strategies were effective in retarding the rate of saltwater intrusion, they appear unable to reverse the increase in salinity levels. Nevertheless, a closer look at the 2 modeling frameworks shows major differences between them. The mechanistic model clearly has a better spatial and temporal resolution and thus can be used to predict salinity levels in 3D space on a daily basis and can identify processes like upconing and the progression of the saltwater wedge. Yet, its prediction uncertainties were large due to the sparsity of available data needed for calibration. Moreover, its computational requirements and run times prohibited its use as an effective decision support tool for stakeholders. In comparison, the developed DBN did not account for spatial variabilities and coarsely represented time. While these simplifications limit the set of questions that the model can answer, the developed DBN was a controllable and parsimonious model whose spatio-temporal space was defined specifically to align with the identified core management problems (Marcot et al. 2006; Pollino and Henderson 2010).

Moreover, the developed model clearly showed the importance of BNs in data-poor regions, where significant expert knowledge (and uncertainty) can be elicited and used to guide model development, provide transparent predictions at meaningful endpoints, as well as identify gaps and the relative sensitivities of decisions to parameter uncertainties. The developed DBN also proved to be a metamodeling tool (Barton et al. 2008) that successfully integrated interdisciplinary knowledge and a diverse set of information types (expert elicitation, multiple linear regression model predictions, field data, and mass balance model). It also allowed for the inclusion of uncertainties both in the model parametrization and in describing the strengths of certain pathways, thus allowing for a transparent evaluation of uncertainties that can be easily communicated with stakeholders. These features are some of the main reasons behind the increased interest in adopting BN in environmental and resource management applications (Bromley et al. 2005; Barton et al. 2008; Pollino and Henderson 2010; Fienen et al. 2013; Death et al. 2015; Chee et al. 2016; Moe et al. 2016; Couture et al. 2018; Gine-Garriga et al. 2018; Uusitalo et al. 2018).

The developed DBN complements and builds upon previous applications of BN that modeled water quality changes (Fienen et al. 2013; Couture et al. 2018; Marcot and Penman 2019). While several of these studies have attempted to incorporate the effect of time (Molina et al. 2013; Orphanou et al. 2014; Chee et al. 2016; Moe et al. 2016), this current application is probably the most developed. It adopted time-slicing and the generation of time clones of certain nodes to allow the system to evolve over time. Yet, even this implementation still has several limitations (refer to the limitation section). The seamless integration of time in BN remains an active research topic and its advancement will increase the penetration of BN in the environmental field, where most environmental variables experience significant changes over time. The current DBN was developed to be fit-for-purpose and ready for use by local coastal managers as a decision support tool for more informed and all-inclusive decision making in the studied aquifer. Nevertheless, while the states, prior probabilities, and CPTs of the model were populated with data relevant to the pilot aquifer, the DAG represents a generic model that describes the main pathways of saltwater intrusion in any coastal setting. Hence, it can be easily transferable to other coastal aquifers subject to the update of selected nodes to reflect the new context.

Limitations

In line with limitations reported in the BN literature (Sperotto et al. 2017), the development of this model and its application faced several limitations, including the availability

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of data, the need to discretize continuous variables, difficulties associated with model representation, and the challenges of implementing quantitative validation and sensitivity analysis. To overcome data limitations, domain expert elicitation proved to be effective in constructing causal links and populating the resulting CPTs (Table 1; Supplemental Data I). Yet, future efforts should focus on collecting field-based data to validate expert judgment when possible. The approach proposed by Pollino et al. (2007) should prove useful toward combining real data with the elicited information once field data become available. Regarding discretization, the model incorporated several continuous variables. Yet, they were all discretized taking into account natural thresholds and management significant cutoffs (Table 1). The sensitivity of the model results to the adopted discretization was not analyzed in this study and should be the focus of future work. The impact that discretization may have on information loss has been highlighted by several studies that recommended a verification process to ensure that the conclusions made are not an artifact of the adopted discretization approach (Ames et al. 2005; Death et al. 2005; Alameddine et al. 2011; Nojavan et al. 2017).

Our model, like most BNs, was not quantitatively validated. Validating forecast models is not possible given the absence of future data; yet some attempt to validate models through assessing hindcast skills (Marcot 2012). In this paper, validation was restricted to rigorous peer review and model reconciliation through a qualitative assessment of model resilience against changes of inputs (Moe et al. 2016). The validation of BN remains to date a major challenge and shortcoming of most environmental BN models, largely due to data scarcity and the dependence of the model (or parts of it) on expert judgment. Even when data are available, the ability to conduct cross-validation is often limited given the increase in model size and the associated data needed to fully parameterize the CPTs. As such, and while several validation approaches have been proposed (e.g., error rates and confusion tables, AUC, k-fold cross validation, spherical payoff, Schwartz's Bayesian Information Criterion, Cohen's Cappa), and some have even been successfully implemented in several of the major BN commercial software (Marcot 2012), model validation remains infrequent (Barton et al. 2008; Aguilera et al. 2011; Moe et al. 2016).

The simplistic treatment of space and time in the developed DBN also limited its predictive skill and the type of questions it can answer. All BN models make an implicit assumption about their modeled geographical and temporal scales (Barton et al. 2008). Our model assumes that the whole study area is underlain by a homogenous aquifer. This disregards the true heterogeneous karstic nature of the aquifer and assumes that the internal and external stresses along with the possible management actions will all have a uniform impact on the entire domain space. Evidently, this is an oversimplification of reality. Nonetheless, consultations with the domain experts confirmed that such a simplification was tolerated as it provides predictions at the scale of the management problem. Yet, it should be clear that the model should not be misused to downscale predictions to spatial scales where uncounted for finer spatial drivers and intermediary nodes become important. Regarding the treatment of time in the model, time-slicing proved to be an effective approach to incorporate time in the BN model and to transform it into a DBN. Yet, the DBN is limited to connecting related variables over time slices and thus assumes that the relationships remain largely fixed. Accordingly, the use of the term "dynamic" could be misunderstood for dynamic modeling rather than for temporal progression in the DBN. Finally, while this model proved to be effective toward assessing the impacts of different management decisions on aquifer salinity and salinity-related socioeconomic costs, there is still a need to further develop the existing model toward transforming it from a DBN into an influence diagram model in order to facilitate decision making under uncertainty with a fully integrated cost-benefit analysis capabilities. Unfortunately, existing software do not support time-slicing within influence diagram models.

CONCLUSION AND WAY FORWARD

A first attempt at developing a decision support tool for the management of and adaptation to SWI using Bayesian networks is presented. The DBN proved effective in analyzing complex systems, while catering for the dynamics and uncertainties associated with data sparsity and imperfect knowledge. Its application on the lifecycle of SWI provided a valid representation of the interaction of multilayered factors and impacts with corresponding uncertainties and interdependence. It exhibited robustness in accommodating a series of scenarios with and without management options confirming its suitability as a decision support tool. Furthermore, it was able to compete with a data and simulation intensive 3D model to represent complex processes and reliably inform decision making in data-scarce aquifers. while offering the advantage of flexibility and transferability under an integrative platform.

The DBN results showed that while the impacts of the projected future climate change significantly increased aquifer salinity and socioeconomic burden, they proved to be secondary when compared to anthropogenic stressors. While demand and supply management options exhibited promise in halting the progress of SWI, none could bring the system to full recovery. Demand management options promise better potential outcomes than supply scenarios, but their implementation is challenging as they require much awareness as well as cultural and behavioral shifts to ensure that the poor are not disproportionately disadvantaged. Meanwhile, supply scenarios provide a faster engineered fix that often requires greater investments. As such, a combination of balanced supply and demand measures is inevitable to control SWI, but in either case, implementation delays were shown to significantly reduce the cost-effectiveness of any intervention.

Future work should explore the sensitivity of the results to the discretization process with additional testing when new temporal data sets are available. Transfer to aquifers with no

or early signs of salinization and/or under different use patterns (i.e., agricultural) can also ensure wider applicability of the model. Further development of the developed model toward an influence diagram model will facilitate decision making under uncertainty with full integration of the cost-benefit analysis.

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Data Availability Statement—Data and associated metadata and calculation tools are available upon request by contacting corresponding author Ibrahim Alameddine (ia04@aub.edu.lb).

SUPPLEMENTAL DATA

Supplemental data include the full details of the network along with its temporal clones, conditional probability tables, equations, and the model's sensitivity analysis.

ORCID

Ibrahim Alameddine http://orcid.org/0000-0002-8974-1985
Majdi Abou Najm http://orcid.org/0000-0002-8434-2520
Song Qian http://orcid.org/0000-0002-2346-4903
Mutasem El-Fadel http://orcid.org/0000-0003-2379-9006

REFERENCES

Abdel Basit S. 1971. Study of groundwater qualtiy in beirut and suburbs [Master's thesis]. Beirut (LB): American Univ of Beirut.

Abou Zakhem B, Kattaa B. 2017. Overexploitation and cumulative drought trend effect on Ras El Ain karstic spring discharge (Khabour Sub-basin, Syria). *J Earth Syst Sci* 126:93.

Acra A, Milki R, Karahagopian Y, Raffoul Z. 1997. Supplementary water from private wells in Gretaer Beirut: A 1982 survey in retrospet. *Int J Environ Stud* 52(1/4):321–334.

Aguilera P, Fernandez A, Fernandez R, Runi R, Salmeron A. 2011. Bayesian networks in environmental modelling. *Environ Model Softw* 26(12): 1376–1388.

Alameddine I, Cha Y, Reckhow K. 2011. An evaluation of automated structure learning with Bayesian networks: An application to estuarine chlorophyll dynamics. *Environ Model Softw* 26(2):163–172.

Alameddine I, Tarhini R, El-Fadel M. 2018. Household economic burden from seawater intrusion in coastal urban areas. *Water Inter* 43(2):217–236.

Allow KA. 2012. The use of injection wells and a subsurface barrier in the prevention of seawater intrusion: A modelling approach. *Arab J Geosci* 5:1151–1161.

Ames DP, Neilson BT, Stevens DK, Lall U. 2005. Using Bayesian networks to model watershed management decisions: An East Canyon Creek case study. *J Hydroinform* 7(4):267–282.

Atlas Climatique du Liban. 1977. Atlas Climatique du Liban. Beirut (LB): Ministry of Public Works and Transport, Republic of Lebanon. 35 p.

Attwa M, Gemail K, Eleraki M. 2016. Use of salinity and resistivity measurements to study the coastal aquifer salinization in a semi-arid region: A case study in the northeast Nile Delta, Egypt. *Environ Earth Sci* 75:784–803.

Ayash B. 2010. Assessment of the quality of private wells used as complementary domestic water sources in beirut [Master's thesis]. Beirut (LB): American Univ of Beirut.

Barton DN, Saloranta T, Moe SJ, Eggestad HO, Kuikka S. 2008. Bayesian belief networks as a meta-modelling tool in integrated river basin management—Pros and cons in evaluating nutrient abatement decisions under uncertainty in a Norwegian river basin. *Ecol Econ* 66(1):91–104.

Bates B, Kunderzewicz Z, Wu S, Palutikof J. 2008. Climate change and water. Geneva (CH): IPCC. 210 p.

Bobba AG. 2002. Numerical modeling of salt-water intrusion due to human activities and sea-level change in the Godavari Delta, India. *Hydrol Sci* 47(S): S67–S80.

Borsuk M, Stow C, Reckhow K. 2004. A Bayesian network of eutrophication models for synthesis, prediction and uncertaintiy analysis. *Ecol Modell* 173(2–3):219–239.

Bromley J, Jackson NA, Clymer OJ, Giacomello AM, Jensen FV. 2005. The use of Hugin to develop Bayesian networks as an aid to integrated water resource planning. *Environ Model Softw* 20(2):231–242.

Cain J. 2001. Planning improvements in natural resources management guidelines for using Bayesian networks to support the planning and management of development programmes in the water sector and beyond. Wallingford (UK): Centre for Ecology and Hydrology. 132 p.

Capaccioni B, Didero M, Paletta C, Didero L. 2005. Saline intrusion and refreshening in a multilayer coastal aquifer in the Catania Plain (Sicily, Southern Italy): Dynamics of degradation processes according to the hydrochemical characteristics of groundwaters. *J Hydrol* 307(1–4):1–16.

Carretero S, Rapaglia J, Bokuniewicz H, Kruse E. 2013. Impact of sea-level rise on saltwater intrusion length into the coastal aquifer, Partido de La Costa, Argentina. *Cont Shelf Res* 61–62:62–70.

CAS. 2008. Statistical yearbook 2007. Beirut (LB): Central Administration for Statistics. 155 p.

Catenacci M, Giupponi C. 2013. Integrated assessment of sea-level rise adaptation strategies using a bayesian decision netwrok approach. *Environ Model Softw* 44:87–100.

CDR/DAR. 2014. Environmental and social impact analysis of the Greater Beirut water supply project. Beirut (LB): Dar El Handasah/Council of Development and Reconstruction. 590 p.

Chang S, Clement T, Simpson M, Lee K. 2011. Does sea-level rise have an impact on saltwater intrusion? *Adv Water Resour* 34(10):1283–1291.

Characklis G, Griffin R, Bedient P. 2005. Measuring the long term regional benefits of salinity reduction. *J Agr Resour Econ* 30(1):69–93.

Chee YE, Wilkinson L, Nicholson AE, Quintana-Ascencio PF, Fauth JE, Hall D, Ponsio KJ, Rumpff L. 2016. Modelling spatial and temporal changes with GIS and spatial and Dynamic Bayesian. *Networks. Environ Model Softw* 82:108–120.

Chen SH, Pollino CA. 2012. Good practice in Bayesian network modelling. *Environ Model Softw* 37:134–145.

Clemen RT. 1991. Making hard decisions: An introduction to decision analysis. Boston (MA): PWS-Kent Publishing Company. 664 p.

Cobaner M, Dogan A, Motz L. 2012. Three dimensional simulation of seawater intrusion in coastal aquifers: A case study in the Goksu Detaic Plain. *J Hydrol* 464–465:262–280.

Comair F. 2010. Water resources in Lebanon: Characterization, water balance and constraints. *Inter J Water Res Dev* 16(4):615–638.

Connor J, Schwabe K, King D. 2012. Irrigated agriculture and climate change: The influence of water supply variability and salinity on adaptation. *Ecol Econ* 77:149–157.

Conrad P, Roehl E, Sexton C, Tufford D, Carbone G, Dow K, Cook J. 2010. Estimating salinity intrusion effects due to climate change along the grand strand of the South Carolina coast. [accessed 2020 Nov 4]. http://acwi.gov/sos/pubs/2ndJFIC/Contents/7E_Conrads_12_20_09_final.pdf

Constantine K, Massoud M, Alameddine I, El-Fadel M. 2017. The role of the water tankers market in water stressed semi-arid urban areas: Implications on water quality and economic burden. *J Environ Manage* 188:85–94.

Couture RM, Moe SJ, Lin Y, Kaste O, Haande S, Solheim AL. 2018. Simulating water quality and ecological status of Laje Vansjo, Norway, under land use and climate change by linking process-orented modeds with a Bayesian network. *Sci Total Environ* 621:713–724.

Cuddy S, Pollino C, Tighe M, Jakeman T, Andrews A, Davis R, Whitfield S, Raine C, Brown J. 2007. Implications of climate change for natural resource management in Central West catchment. ICAM Centre, The

Australian National University. Canberra (AU): The Integrated Catchment Assessment and Management Centre (iCAM).
De Montety V, Radakovitch O, Vallet-Coulomb C, Blavoux B, Hermitte D, Valles V. 2008. Origin of groundwater salinity and hydrogeochemical processes in a confined aquifer: Case of the Rhone delta (Southern France). *J Appl Geochem* 23(8):2337–2349.
de Santa Olalla FM, Dominguez A, Ortega F, Artigao A, Fabeiro C. 2007. Bayesian networks in planning a large aquifer in Eastern Mancha, Spain. *Environ Model Softw* 22(8):1089–1100.
Death RG, Death F, Stubbington R, Joy M, van den Belt M. 2015. How good are Bayesian belief networks for environment management? A test with data from an agricultural river catchment. *Freshw Biol* 60(11):2297–2309.
Eissa MA, Mahmoud HH, Shouakar-Stash O, El-Shiekh A, Parker B. 2016. Geophysical and geochemical studies to delineate seawater intrusion in Bagoush area, Northwestern Coast, Egypt. *J Afr Earth Sci* 121:365–381.
El-Fadel M, Abu Najm M, Alameddine I, Momjian N, Bahnan A. 2015. Managed aquifer recharge in the Hazmieh area to prevent seawater intrusion in Beirut—Lebanon. Bonn (DE): Deutsche Gesellschaft fur Internationale Zusammenarbeir GIZ. 222 p.
El Fadel M, Alamedine I, Abu Najm M, Zurayk R, Doummar J, Massoud M, Chaaban J, Jamali D, Rachid G, Maroun R et al. 2015. Climate change and saltwater intrusion along the Eastern Mediterranean: Socio-economic vulnerability and adaptation. Beirut (LB): American Univ of Beirut. Final Report 106706-001. [accessed 2020 Nov 4]. https://www.idrc.ca/en/project/climate-change-and-saltwater-intrusion-along-eastern-mediterranean-socioeconomic
El-Fadel M, Massoud M, Kalinian H. 2000. Screening groundwater quality in Lebanon: A preliminary assessment. Beirut (LB): Water Resource Center (AUB). USAID Report.
El Hassadi A. 2008. Seawater intrusion in Derna located in the Green Mountain region, Libya—A threatening recurrent phenomenon calling for desalination. *Desalination* 220(1–3):189–193.
El-Samra R, Bou-Zeid E, Banalath HK, Stenchikov G, El-Fadel M. 2016. Future intensification of hydro-meteorological extremes: Downscaling using the weather research and forecasting model. *Clim Dyn* 49(11–12):3765–3785.
El Shinnawy I, Abayazid H. 2011. Vulnerability assessment of climate change impact on groundwater salinity in the Nile Delta coastal region, Egypt. In: Conference on Coastal Engineering Practice 2011; 2011 August 21–24; San Diego, CA. p 422–435.
El Yaouti FE, El Mandour A, Khattach D, Benavente J, Kaufmann O. 2009. Salinization processes in the unconfined aquifer of Bou-Areg (NE Morocco): A geostatistical, geochemical and tomographic study. *J Appl Geochem* 24(1):16–31.
EnviroLink. 2011. New Zealand guidelines for the monitoring and management of seawater intrusion risks on groundwater. Christchurch (NZ): Pattle Delamore Partners LTD. 108 p.
[ESCWA] Economic and Social Commission for Western Asia. 2005. Urbanization and the changing character of the Arab city. New York (NY). E/ESCWA/SDD/2005/1. 46 p.
Eurie Forio M, Landuyt D, Bennetsen E, Lock K, Nguyen THT, Ambarita MND, Musinge PLS, Boets P, Everaert G, Dominguez-Granda L et al. 2015. Bayesian belief network models to analyse and predict ecological water quality in rivers. *Ecol Model* 312:222–238.
[FAO] Food and Agriculture Organization of the United Nations. 1997. Seawater intrusion in coastal aquifers: Guidelines for study, monitoring and control. Rome (IT). Water Report 11. 161 p.
Faour G, Mhawej M. 2014. Mapping urban transitions in the Greater Beirut area using different space platforms. *Land* 3(3):941–956.
Fatoric S, Chelleri L. 2012. Vulnerability to the effects of climate change and adaptation: The case of the Spanish Ebro Delta. *Ocean Coast Manag* 60:1–10.
Fenton N, Neil M. 2012. Risk assessment and decision analysis with Bayesian networks. Boca Raton (FL): CRC Press. 527 p.
Ferguson G, Gleeson T. 2012. Vulnerability of coastal aquifer to groundwater uses and climate change. *Nat Clim Change* 2:342–345.
Fienen M, Masterson J, Plant N, Gutierrez B, Thieler E. 2013. Bridging groundwater models and decision support with a Bayesian network. *Water Resour Res* 49(10):6459–6473.
Frank K, Boyer T, 2014. Coastal utilities' response to saltwater intrusion. Gainesville (FL): Univ of Florida, Gainesville. [accessed 2020 Nov 4]. http://floridawca.org/sites/default/files/documents/Presentation_Casler_Saltwater%20Intrusion%20Survey%20FL%20WCA%20Workshop.pdf
Gine-Garriga R, Requejo D, Molina J, Perez-Foguet A. 2018. A novel planning approach for the water, sanitation and hygiene (WASH) sector: The use of object-oriented Bayesian networks. *Environ Model Softw* 103:1–15.
Giordano R, D'Agostino D, Apollonio C, Lamaddalena N, Vurro M. 2013. Bayesian belief network to support conflict analysis for groundwater protection: The case of the Apulia region. *J Environ Manage* 115:136e146.
Gonzalez-Redin J, Luque S, Poggio L, Smith R, Gimona A. 2016. Spatial Bayesian belief networks as a planning decision tool for mapping ecosystem services trade-offs on forested landscapes. *Environ Res* 144(Part B): 15–26.
Goodchild CW. 2007. Modelling the impact of climate change on domestic water demand. *Water Environ J* 17(1):8–12.
Hall J, Twyman CKA. 2005. Influence diagrams for representing uncertainty in climate related propositions. *Clim Change* 69(2/3):343–365.
Harbor J. 1994. A practical method for estimating the impact of land-use change on surface runoff, groundwater recharge and wetland hydrology. *J Am Plann Assoc* 60(1):95–108.
Howitt R, Medellín-Azuara J, MacEwan D. 2009. Estimating the economic impacts of agricultural yield related changes for California. Sacramento (CA): California Climate Change Center. Report CEC-500-2009-042-F. 40 p.
Ivkovic KM, Marshall SK, Carey H, Morgan LK, Sundaram B, Dixon-Jain P, Caruana L, Garlapati N, Werner AD. 2012. National scale vulnerability assessment of seawater intusion: Summary report. Canberra (AU): National Water Commission. Waterlines Report Series No 85.
Jackson C, Meister R, Prudhomme C. 2011. Modelling the effects of climate change and its uncertainity on UK Chalk groundwater resources from an ensemble of global climate model predictions. *J Hydrol* 399(1–2): 12–28.
Jarboo M, Al-Najar H. 2015. Climate change and its impact on domestic water consumption in sub-urban regions in the Gaza Strip. *Int J Clim Chang Str* 7(1):3–16.
Javadi AA, Abd-Elhamid HF, Farmani R. 2012. A simulation-optimization model to control seawater intrusion in coastal aquifers using abstraction/recharge wells. *Int J Numer Anal Meth Geomech* 36(16):1757–1779.
Kashuba RO. 2010. Bayesian methods to characterize uncertainty (Doctoral dissertation). Durham (NC): Duke Univ.
Keshtkar AR, Salajegheh A, Sadoddin A, Allan MG. 2013. Application of Bayesian networks for sustainability assessment in catchment modeling and management (case study: The Hablehrood river catchment). *Ecol Modell* 268:48–54.
Khair K. 1992. The effects of overexploitation on coastal aquifers in Lebanon. *Int Assoc Hydrogeo* 3:349–362.
Kjaerulff UB, Madsen AL. 2008. Bayesian networks and influence diagrams, a guide to construction and analysis. New York (NY): Springer. 382 p.
Konikow L, Reilly T. 1999. Seawater Intrusion in the United States. In: Bear J, Cheng AHD, Sorek S, Ouazar D, Herrera I, editors. Seawater intrusion in coastal aquifers: Concepts, methods and practices. New York (NY): Springer. p 463–506.
Koussis A, Mazi K, Destouni G. 2012. Analytical single potential sharp interface solutions for regional saltwater intrusion in sloping unconfined coastal aquifers, with pumping and recharge. *J Hydrol* 416/417:1–11.
Kragt ME. 2009. A beginners guide to Bayesian network modelling for integrated catchment management. Brisbane (AU): Landscape Logic. Report 9. 22 p.
Kragt ME, Newham LTH, Jakeman AJ. 2009. A Bayesian network approach to integrating economic and biophysical modelling. In: 18th World IMACS/MODSIM Congress; 2009 July 13–17; Cairns, AU. p 2377–2383.
Levi E, Goldman M, Tibor G, Herut B. 2018. Delineation of subsea freshwater extension by marine geoelectromagnetic soundings (SE Mediterranean SEA). *Water Res Manage* 32(4):3765–3779.
Li X, Zhang Y, Guo F, Gao X, Wang Y. 2018. Predicting the effect of land use and climate change on stream macroinvertebrates based on the linkage

between structural equation modeling and Bayesian network. *Ecol Indicat* 85(5):820–831.

Lucena-Moya P, Brawata R, Kath J, Harrison E, ElSawah S, Dyer F. 2015. Discretization of continuous predictor variables in Bayesian networks: An ecological threshold approach. *Environ Model Softw* 66:36–45.

Marcot BG. 2012. Metrics for evaluating performance and uncertainty of Bayesian network models. *Ecol Modell* 230:50–62.

Marcot BG, Penman TD. 2019. Advances in Bayesian network modeling: Integration of modeling technologies. *Environ Model Softw* 111:386–393.

[MoE] Ministry of Environment. 2011. Lebanon's Second National Communication to the United Nations Framework Convention on Climate Change. Beirut (LB). Report 2. 228 p.

Moe JS, Haande S, Couture RM. 2016. Climate change, cyanobacteria blooms and ecological status of lakes: A Bayesian network approach. *Ecol Modell* 337:330–347.

[MoE/UNDP] Ministry of Environment and United Nations Development Programme. 2011. State of the environment report. Beirut (LB). Report 3. 353 p.

[MoE/UNDP/GEF] Ministry of Environment, United Nations Development Programme, and Global Environment Facility. 2016. Lebanon Third National Communication Report to the UN Framework Convention on Climate Change. Beirut (LB). Report 3. 237 p.

[MoEW] Ministry of Energy and Water. 2010. National water sector strategy: Supply/demand forecasts. Beirut (LB). [accessed 2020 Nov 4]. http://extwprlegs1.fao.org/docs/pdf/leb166572E.pdf

[MOF/UNDP] Ministry of Finance/United Nations Development Programme. 2017. Assessing labor income inequality in Lebanon's private sector: Findings, comparative analysis of determinants and recommendations. [accessed 2020 Nov 4]. https://www.undp.org/content/dam/lebanon/docs/Governance/Publications/Assessing%20Labor%20Income%20Inequality%20in%20Lebanon%E2%80%99s%20Private%20Sector.pdf

Molina J, Pulido-Velazquez D, Garcia-Arostegui J, Pulido-Velaszquez M. 2013. Dynamic Bayesian networks as a decision support tool for assessing climate change impacts on highly stressed groundwater systems. *J Hydrol* 479:113–129.

Molina JL, Bromley J, Garcia-Arostegui JL, Sullivan C, Benavente J. 2010. Integrated water resources management of overexploited hydrogeological systems using object-oriented Bayesian networks. *Environ Model Softw* 25:383–397.

Morgan MG, Henrion M. 1990. Uncertainty: A guide to dealing with uncertainty in quantitative risk and policy analysis. Cambridge (MA): Cambridge Univ Press. 354 p.

Mushtaha A, Van Camp M, Walraevens K. 2019. Evolution of runoff and groundwater recharge in the Gaza Strip over the last four decades. *Environ Earth Sci* 78:32.

Nasr J, Jurdi M, Chaaya M, El-Fadel M. 2012. Actual and perceived water quality in one of Beirut's main settings: A comparative approach. *IJWREM* 3(1):47–54.

Neukum C, Azzam R. 2012. Impact of climate change on groundwater echarge in a small catchment in the Black Forest, Germany. *Hydrogeol J* 20(3):547–560.

Newton AC. 2009. Bayesian Belief Networks in environmental modelling: A review of recent progress. In: Findley PN, editor. Environmental modelling: New research. New York (NY): Nova Science Publishers. p 13–50.

Nicholls RJ, Hanson S, Herweijer C, Patmore N, Hallegatte S, Corfee-Morlot J, Château J, Muir-Wood R. 2007. Ranking port cities with high exposure and vulnerability to climate extremes—exposure estimates. Paris (FR): OECD Environment Directorate. Working paper No 1. 62 p.

Nojavan FA, Qian S, Paerl H, Reckhow K, Albright E. 2014. A study of anthropogenic and climatic disturbance of the New River Estuary using a Bayesian Belief network. *Mar Pollut Bull* 83(1):107–115.

Nyberg JB, Marcot BG, Sulyma R. 2006. Using Bayesian belief networks in adaptive management. *Can J For Res* 36(12):3104–3116.

Orphanou K, Stassopoulou A, Keravnuo E. 2014. Temporal abstraction and temporal Bayesian networks in clinical domains: A survey. *Artif Intell Med* 60(3):133–149.

Park HY, Jang K, Ju JW, Yeo IW. 2012. Hydrogeological characterization of seawater intrusion in tidally forced coastal fractured bedrock aquifer. *J Hydrol* 446–447:77–89.

Pearl J. 1988. Probabilistic reasoning in intelligent systems: Networks of plausible inference. Burlington (MA): Morgan Kaufmann. 576 p.

Peltekian A. 1980. Groundwater quality of Greater Beirut in relation to geologic structure and the extent of seawater intrusion [Master's thesis]. Beirut (LB): American Univ of Beirut.

Phan TD, Smart JCR, Capon SJ, Hadwen WL, Sahin O. 2016. Applications of Bayesian belief networks in water resource management: A systematic review. *Environ Model Softw* 85:98–111.

Pollino CA, Henderson C. 2010. Bayesian networks: A guide for their application in natural resource management and policy. Technical report No 14. Landscape Logic, Department of the Environment, Water, Heritage and the Arts, Australian Government.

Pollino CA, Woodberry O, Nicholson A, Korb K, Hart BT. 2007. Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment. *Environ Model Softw* 22(8):1140–1152.

Purandara B, Venkatesh B, Choubey V. 2010. Estimation of groundwater recharge under various land use and land covers in parts of Western Ghat, Karnataka, India. *Mater Geoenviron* 57(2):181–194.

Rachid G, El-Fadel M, Abou Najm M, Alameddine I. 2017. Towards a framework for the assessment of saltwater intrusion in coastal aquifers. *Environ Impact Assess Rev* 67:10–22.

Radl A, Lexer MJ, Vacik H. 2018. A Bayesian Belief Network approach to predict damages caused by disturbance agents. *Forest* 9(1):15.

Ragan GE, Young RA, Makela CJ. 2000. New evidence on the economic benefits of controlling salinity in domestic water supplies. *Water Resour Res* 36(4):1087–1095.

Rahman MM, Hagare D, Maheshwari B. 2014. Framework to assess sources controlling soil salinity resulting from irrigation using recycled water: An application of Bayesian belief network. *J Clean Prod* 105:406–419.

Reilly T, Goodman A. 1985. Quantitative analysis of saltwater-freshwater relationships in groundwater systems—A historical perspective. *J Hydrol* 80(1–2):125–160.

Saadeh M. 2008. Influence of overexploitation and seawater intrusion on the quality of groundwater in Greater Beirut [Master's thesis]. Aachen (DE): RWTH Aachen Univ.

Saadeh M, Wakim E. 2017. Deterioration of groundwater in Beirut due to seawater intrusion. *J Geosci Environ Prot* 5(11):149–159.

Sadoddin A, Letcher RA, Jakeman AJ, Newham LTH. 2005. A Bayesian decision network approach for assessing the ecological impacts of salinity management. *Math Comput Simul* 69(1e2):162e176.

Safi A, Rachid G, El-Fadel M, Doummar J, Abu Najm M, Alameddine I. 2018. Synergy of climate change and local pressures on saltwater intrusion in coastal urban areas: Effective adaptation for policy planning. *Water Inter* 43(2):145–164.

Saidy M. 2016. Desalination for water shortage in the greater beirut area: A cost benefit comparative assessment with economy of scale and environmental externalities [Master's thesis]. Beirut (LB): American Univ of Beirut.

Sales RJ. 2009. Vulnerability and adaptation of coastal communities to climate variability and sea-level rise: Their implications for integrated coastal zone management of Cavite City, Philippines. *Ocean Coast Manag* 52:395–404.

Sanford A, Pope P. 2010. Current challenges using models to forecast seawater intrusion: Lessons from the Eastern Shore of Virginia. *Hydrogeol J* 18(1):73–93.

Selmi A. 2013. Water management and modeling of a coastal aquifer—Case study (Gaza Strip) [PhD thesis]. Milan (IT): Univ of Milan Bicocca.

Sherif M, Kacimov A, Javadi A, Ebraheem A. 2012. Modeling groundwater flow and seaswater intrusion in the coastal aquifer of Wadi Ham, UAE. *Water Resour Manag* 26(3):751–774.

Sophiya M, Syed T. 2013. Assessment of vulnerability to seawater intrusion and potenital remediation measures for coastal aquifers: A case study from eastern India. *Environ Earth Sci* 70:1197–1209.

Sperotto A, Molina JL, Torresan S, Critto A, Marcomini A. 2017. Reviewing Bayesian networks potentials for climate change impacts assessment and

management: A multi-risk perspective. *J Environ Manag* 202(Part 1): 320–331.

Talukder RR, Rutherford S, Phung D, Islam MZ, Chu C. 2016. The effect of drinking water salinity on blood pressure in young adults of coastal Bangladesh. *Environ Pollut* 214:248–254.

Tribbia J, Moser SC. 2008. More than information: What coastal managers need to plan for climate change. *Environ Sci Pol* 11(4):315–328.

tu.tiempo. 2016. World Weath. [accessed 2020 Jun 25]. https://en.tutiempo.net/

Ur Rahman T, Rasheduzzaman M, Habib MA, Ahmed A, Tareq SM, Muniruzzaman SM. 2017. Assessment of fresh water security in coastal Bangladesh: An insight from salinity, community perception and adaptation. *Ocean Coast Manag* 137:68–81.

Uusitalo L. 2007. Advantages and challenges of Bayesian networks in environmental modelling. *Ecol Modell* 203(3–4):312–318.

Uusitalo L, Tomczak MT, Müller-Karulis B, Putnis I, Trifonova N. 2018. Hidden variables in a dynamic Bayesian network identify ecosystem level change. *Ecol Inf* 45:9–15.

[WB] World Bank. 2010. Republic of Lebanon—Water sector: Public expenditure review. Washington (DC). [accessed 2020 Nov 4]. https://openknowledge.worldbank.org/handle/10986/2877

[WB] World Bank. 2017. Greater Beirut water supply project. Implementation status & results report. Washington (DC). Report ISR28472. 10 p.

Werner AD, Bakker M, Post V, Vandenbohede A, Lu C, Ataie-Ashtiani B, Simmons C, Barry DA. 2013. Seawater intrusion processes, investigation and management: Recent advances and future challenges. *Adv Water Resour* 51:3–26.

Whitcomb JB. 2005. Florida water rates evaluation of single-family homes. Brooksville (FL): Florida Water Management Districts. 113 p.

Wilson SM. 2004. Dryland and urban salinity costs across the Murray-Darling basin: An overview and guidelines for identifying and valuing impacts. Canberra (AU): Murray-Darling Basin Commission. 128 p.

Winkler RL. 2003. An introduction to Bayesian inference and decision. 2nd ed. Gainesville (FL): Probabilistic Publishing. 464 p.

Wu J, Xu S, Zhou R, Qin Y. 2016. Scenario analysis of mine water inrush hazard using Bayesian networks. *Saf Sci* 89:231–239.

Zaarour T. 2017. Application of GALDIT index in the Mediterranean region to assess vulnerability to seawater intrusion [Master's thesis]. Lund (SE): Lund Univ.

Zandona A, Vasta R, Chio A, DiCamillo B. 2019. A dynamic Bayesian network model for the simulation of amyotrophic lateral sclerosis progression. *BMC Bioinformatics* 20:118.

Zhang E, Savenije H, Wu H, Kong Y, Zhu J. 2011. Analytical solution for salt intrusion in the Yangtze Estuary, China. *Estuar Coast Shelf Sci* 91(4): 492–501.

