Environmental Modelling and Software 168 (2023) 105764

Contents lists available at ScienceDirect

Environmental Modelling and Software

journal homepage: www.elsevier.com/locate/envsoft

Participatory Bayesian Network modeling of climate change risks and adaptation regarding water supply: Integration of multi-model ensemble hazard estimates and local expert knowledge

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ARTICLE INFO

Keywords:
Bayesian network
Climate change
Risk assessment
Multi-model ensemble
Uncertainty
Participatory process
Roadmap

ABSTRACT

Local climate change risk assessments (LCCRAs) are best supported by a quantitative integration of physical hazards, exposures and vulnerabilities that includes the characterization of uncertainties. We propose to use Bayesian Networks (BNs) for this task and show how to integrate freely-available output of multiple global hydrological models (GHMs) into BNs, in order to probabilistically assess risks for water supply. Projected relative changes in hydrological variables computed by three GHMs driven by the output of four global climate models were processed using MATLAB, taking into account local information on water availability and use. A roadmap to set up BNs and apply probability distributions of risk levels under historic and future climate and water use was co-developed with experts from the Maghreb (Tunisia, Algeria, Morocco) who positively evaluated the BN application for LCCRAs. We conclude that the presented approach is suitable for application in the many LCCRAs necessary for successful adaptation to climate change world-wide.

Software and data availability

For the case study, three softwares were used: Netica, Matlab, and DANA.

1. Name of software: Netica, 5.24" 64 Bit, For MS Windows 7 to 10
   - Developer: Norsys Software Corp.
   - Contact information: www.norsys.com
   - Hardware requirements: PC/Mac
   - Availability: https://www.norsys.com/netica.html
   - Cost: license necessary
2. Name of software: Matlab R2019a
   - Developer: The MathWorks, Inc.
   - Contact information: https://www.mathworks.com/
   - Hardware requirements: PC/Mac/Linux
   - Availability: https://www.mathworks.com/products/matlab.html
   - Cost: license necessary
3. Name of software: DANA
   - Developer: Pieter W.G. Bots, Delft University of Technology, Faculty of Technology, Policy and Management
   - Contact information: http://dana.actoranalysis.com
   - First year available: 2000
   - Hardware requirements: PC (Windows)
   - Program size: 2.01 MB
   - Availability: http://dana.actoranalysis.com/
   - Cost: license but at no cost

The input of multi-model ensemble data used in the case study is provided in the supplemental Excel-file; Multi-model ensemble data of the output of hydrological – but also of other types of – global-scale impact models is also freely available from ISIMIP (www.isimip.org). All other data obtained from literature or expert knowledge is listed in the paper.

1. Introduction

For successful climate change adaptation, decision makers need appropriate information about the risks of climate change impacts. According to IPCC (2014), the *risk* that a certain impact (adverse

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https://doi.org/10.1016/j.envsoft.2023.105764
Received 1 December 2022; Received in revised form 5 June 2023; Accepted 15 June 2023
Available online 3 July 2023

consequence for a natural or human system) of climate change occurs results from the interaction of *hazard* (potentially occurring physical event or trend as affected by climate change), *exposure* (presence of people, ecosystems and assets) and *vulnerability* (predisposition to be adversely affected). Risk is often estimated as the probability of occurrence of hazardous events or trends multiplied by the negative impacts that ensue if the event or trend occurs (IPCC, 2014). To assess climate change risks, climate change hazards, exposures, vulnerabilities and their uncertainties, i.e., for example in the form of probabilities, need to be characterized (Döll et al., 2015). Climate change hazards related to freshwater are best characterized by changes of hydrological variables (due to climate) that are relevant for the specific risk considered; for example, climate-driven changes in groundwater recharge and net irrigation requirement would be relevant for characterizing risks of climate change for irrigation water supply from groundwater.

Projections of changes of hydrological variables vary widely even for specified greenhouse gas emission scenarios because of the significant uncertainties of both climate and hydrological modeling; to characterize climate change hazards, it is therefore state-of-the-art to rely on multi-model ensembles for quantifying potential future changes in hydrological variables (Döll et al., 2015). The ensemble output can be used to, e.g., compute mean or median changes of these projections, and moreover, analyze agreement of models regarding projected changes or compute percentiles of model output that can roughly be interpreted as probabilities (Döll et al., 2015). Such ensembles have been generated in the framework of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) initiative (e.g., Frieler et al., 2017), where the bias-adjusted output of several global climate models for various greenhouse gas emissions scenarios was used as the input to several global hydrological models (GHM) to compute time series of historic and potential future values of hydrological variables. The model output of the simulation round ISIMIP2b is freely available (https://www.isimip.org/outputdata/). In addition, CO-MICC (www.co-micc.eu) is a web portal that freely provides similar model output for download, in addition to interactive online visualization.

The disadvantage of global hydrological models for local climate change risk assessments (LCCRA) is that they may only roughly represent current local hydrological conditions, mainly owing to the low spatial resolution of mostly 0.5° latitude by 0.5° longitude (55 km by 55 km at the equator) and their restricted representation of anthropogenic alterations of the water cycle by e.g. water use, man-made reservoirs and water transfers. Their obvious advantage is that they cover land areas of the Earth globally (except Antarctica and Greenland) and can therefore help to estimate potential changes in hydrological variables where no local hydrological or water resources model is available. Even if a hydrological model for a specific drainage basin exists that could be driven by the output of a number of Global Climate Models (GCM), additional consideration of an ensemble of GHMs is useful to avoid an underestimation of the range of potential changes due to hydrological model uncertainty. This uncertainty arises, e.g., because the models' simulated changes differ because of different equations for computing potential evapotranspiration (Kingston et al., 2009) or because most local to regional hydrological models do not simulate the response of vegetation to increasing CO_2 concentrations and climate change, a process that strongly determines future evapotranspiration and thus runoff changes (Davie et al., 2013; Gerten et al., 2014). While a few scientific papers on multi-model ensembles of potential changes of hydrological variables due to climate change have been published (e.g., global-scale studies on future streamflow Schewe et al., 2014, irrigation requirements Wada et al., 2013, and groundwater recharge Reinecke et al., 2021), no studies have yet been performed on how to best utilize them in local climate change risk assessments.

Within the climate change adaptation literature, a shift from top-down approaches towards bottom-up approaches has begun to take place (Helgeson, 2020), addressing the importance of the decision context as an interplay between climate and society, and the needs of immediate adaptation decisions (Conway et al., 2019) . A bottom-up approach structures the problem starting from an understanding of the specific decision context rather than the broader climatic conditions under which the chosen action will ultimately play out. It begins with a well-defined objective, defined in terms of a (e.g. policy-) performance measure and a critical threshold that draws a line between adequate and inadequate performance of that measure. Starting from this objective, one works backwards to determine the climatic (or other external) conditions under which the stated performance threshold would be reached and an appropriate policy should be implemented (Helgeson, 2020). A critical threshold is a level of chronic unacceptable performance, which is often identified by stakeholders as they intuitively understand the implications of failure in their system (Mendoza et al., 2018). As climate change involves complex interactions and changing likelihoods of diverse impacts (IPCC, 2014) within these systems, it is essential to define the risks and estimate their probability of occurrence (Borgomeo et al., 2018). To this end, appropriate methods and tools are needed.

Bayesian Networks (BN) are a cutting-edge integrated[1] modeling approach (Terzi et al., 2019) to deal with uncertain and complex domains (Phan et al., 2016) such as climate change (Sperotto et al., 2017) by estimating probabilities of occurring risks. Bayesian Networks are a formal representation of the joint probabilistic behavior of a system conditioned by deeply uncertain but potentially useful information about the future (Taner et al., 2019). They can (1) combine quantitative multi-model output data and qualitative expert knowledge, (2) deal with uncertain multi-model ensemble projections and other uncertain system variables regarding hazard, exposure and vulnerability inherently through their representation with probability distributions, (3) include multiple stressors and endpoints, (4) compute alternative scenarios for water availability and demand, and (5) take into account the effect of adaptation policies on climate change risks (Sperotto et al., 2017). Because of their ability to integrate not only quantitative data but also qualitative expert beliefs, they are also referred to as Bayesian Belief Networks. These make them promising tools to this end of considering complex information in climate change risk assessments.

In the past two decades the use of Bayesian Networks in many environmental fields with a risk assessment perspective has been exponentially growing (Phan et al., 2016) and Bayesian networks are increasingly being integrated with other modeling constructs and tools (Marcot and Penman, 2019). Phan et al. (2016) find 111 original, peer-reviewed papers published from 1997 to 2016 dealing with Bayesian Networks in the field of water resources. Sperotto et al. (2017) review 22 publications dealing with Bayesian Networks for climate change risk (or impact) assessments and management. Eight out of the 22 use Bayesian Networks to integrate both climate change hazards and freshwater, differing in how information on climate change hazards are integrated. Three integrate climate change hazards as generic scenarios such as +50%, +100% or "high"/"low" precipitation change (Varis and Kuikka, 1997; Kotta et al., 2009; Nojavan A. et al., 2014). Five use climate change projections from climate models and quantitative projections from water models to inform the Bayesian Network set-up. Among these studies, Molina et al. (2013) develop a Bayesian Network for assessing climate change impacts on highly stressed groundwater systems in Spain, using seven Regional Climatic Models and one regional hydrological model. Dyer et al. (2014) use Bayesian Networks to investigate the climate change impacts on streamflow and water quality in Australia, using 15 GCMs and one regional hydrological model. Couture et al. (2018) assess the potential future ecological status of a lake in Norway by using two GCMs, one regional hydrological model, one catchment phosphorus model and one lake model. Sperotto et al.

[1] I.e., the ability to link main features from diverse disciplines such as society, economy and physical Earth system processes in one modeling framework.

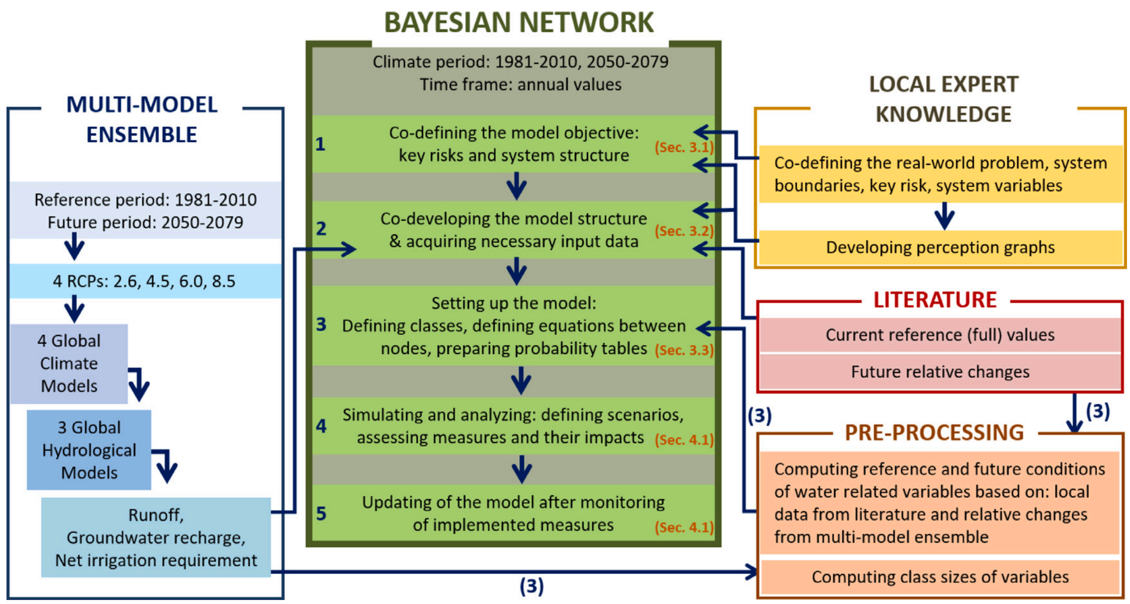


Fig. 1. Steps 1 to 5 (blue numbers) of applying BN modeling in participatory LCCRA, with the three knowledge sources local stakeholder knowledge, multi-model ensemble, and literature, where integration of the latter two required data pre-processing during step 3.

(2019a) assess climate change impacts on nutrient loadings in a river, using projections of a Regional Climate Model and one hydrological model. Sperotto et al. (2019b) extend the study by including ten climate scenarios. As all eight studies applied only one hydrological model, the uncertainty range of future projections of freshwater-related climate change hazards was likely underestimated in the respective Bayesian Networks. All eight publications lack a comprehensive documentation of the methods applied to integrate data of multi-model ensembles into a Bayesian Network model, how to compute the probabilistic links between the variables of the Bayesian Network (i.e. information to feed into the conditional probability tables), and how to compute class sizes of nodes in the Bayesian Network. Only one of the eight studies (Sperotto et al., 2019a) uses the input of experts or stakeholders for conceptualization of the Bayesian Network but a description of how this was done is lacking. However, good practices in Bayesian Network modeling require expert or stakeholder involvement during all steps of the model (co-)development, from model co-conceptualization to co-validation (Bromley et al., 2005).

The objective of this publication is to provide a roadmap for setting up and applying suitable Bayesian Network models in LCCRAs, using a case study about assessing climate change risks for water supply in the Medjerda basin (Tunisia and Algeria). The focus is on a detailed description of (1) how multi-model ensemble estimates of hydrological variables from global hydrological models can be integrated into a Bayesian Network to obtain a state-of-the-art representation of climate change hazards and their uncertainties, and (2) how stakeholders can be involved in the Bayesian Network setup (participatory manner). To this end, we co-designed with local experts a method to set up a Bayesian Network model, by mimicking the participatory stakeholder process that would be conducted in an LCCRA. Involving specific water management experts meant that they could not only take on the roles of stakeholders in the simulated case study but were also able to evaluate the usefulness of the co-design.

An overview of the method is given in Section 2, detailed steps for the setup of the Bayesian Network including the integration of a global hydrological ensemble as data input and a suite of tools in a participatory process with stakeholders are given in Section 3, the simulation results in the case study are exemplarily analyzed in Section 4, while the experts' evaluation, the discussion and the conclusion are presented in Sections 5, 6 and 7, respectively.

2. Method

Scientists and local experts (co)developed the roadmap of the setup by mimicking a participatory process that would happen with stakeholders in an LCCRA. To this end, we use the term "stakeholders" in the setup steps of the roadmap to describe the participatory process as it would be applied in an LCCRA. In addition, we use them as "experts" in an evaluation of the usefulness of the developed method for local climate change risk assessment. Evaluation was conducted using surveys at workshops and is discussed in Section 5.

2.1. Roadmap for setting up and applying Bayesian Network models for LCCRAs

We used Bayesian Network modeling informed by the output of an ensemble of global hydrological models, literature data and local stakeholder knowledge to assess the probabilistic risk of climate change for water supply from groundwater and from surface water (Fig. 1). Our method consisted of a linked chain of tools through five steps: (1) Co-defining the real-world problem, the Bayesian Network model objective, the key risks, and the structure of the system to be modeled, (2) co-developing the Bayesian Network model structure including gathering data from literature and our multi-model ensemble, (3) setting up the Bayesian Network model based on processing with the software tools MATLAB[2] and Netica,[3] and (4) running the Bayesian Network model with Netica to compute and analyze risks under various future conditions, i.e. varying climate change and water use scenarios, including adaptation measures. Lastly, (5) after monitoring of implemented measures, the Bayesian Network model can be updated and then better represent the simulated system. Steps 1–3, pertaining to the setup of the Bayesian Network model, are presented in Section 3, while steps 4–5 are discussed in Section 4.

2.2. Bayesian Network modeling

A Bayesian Network model is a probabilistic graphical model of a real system for which a graph expresses the conditional dependence structure among variables. It consists of three main components:

[2] https://www.mathworks.com/products/matlab.html
[3] https://www.norsys.com/netica.html

Table 1
Stakeholder involvement regarding the setup of the Bayesian network tool.

Type of interaction	Number of local stakeholders	Location	Duration	Date	Topics and activities
Semi-structured stakeholder interviews	13	Tunis (Tunisia) Algiers (Algeria) Marrakesh, Beni Mellal, Casablanca (Morocco)	10 days, 2 h per interview	May 2018	(1) Tasks, responsibilities and challenges of stakeholder's organization (2) Stakeholder's problem perception of the situation and challenges in the country (3) Development of individual perception graphs representing the problem perspective (4) Information needs to support the country in climate change adaptation in the water sector (5) Data availability and needs, time frame for planning of the organization
Workshop I	6	Le Mans (France)	1.5 days	November 2018	(1) Presentation of perception graphs (2) Introduction to Bayesian Networks and presentation of first Bayesian Network structure (3) Acquiring stakeholders' input for knowledge and data provisioning
Workshop II	7	Tunis (Tunisia)	2 days	October 2019	(1) Presentation of further developed Bayesian Network (2) Co-development of possible risk indicators, further variables and qualitative classes

(1) the structure of the Bayesian Network, i.e. a directed acyclic graph that consists of a set of nodes representing the system variables visualized as boxes and a set of arrows indicating the relationships between them (Phan et al., 2016) in a causal network, (2) a set of defined distinct classes of attainable values for each variable (e.g. quantitatively: 1–2 mm, 2–3 mm, 3–4 mm or qualitatively: low, medium, high), and (3) (un)conditional probability tables (CPTs) that represent how one system variable depends on the state of another variable, thus quantifying the links in the graph (Phan et al., 2016). Each variable is described probabilistically, i.e. by the distinct classes and by the probability of the variable belonging to each class (probability distribution). Unconditional, or fixed, probability tables are used for nodes at the start of branches in the causal network, that do not depend on the state of another variable to define their probability distribution (see root nodes below), while the conditional probability tables uniquely determine the probability distribution of all subsequent variables. This roadmap focuses on the explanation of those aspects required to set up the Bayesian Network, the interested reader can find more in-depth explanations of the Bayesian Network method, e.g., in Pearl (1998), Heckerman (1998) and Jensen and Nielsen (2007).

Regarding Bayesian Network terminology, we use in this paper the terms "nodes" (i.e. variables of the system), "classes" (i.e. the possible states within a node), and specifically "parent node" (i.e. a node with child nodes downlink in the graph), "child node" (i.e. with parent nodes uplink in the graph) and "root node" (i.e. a node at the beginning of a branch without any parent nodes).

Our five steps guide the process of generating and entering the required data for the three components of the Network. In general, not enough data are available in complex problem fields to learn CPTs and network structure automatically from data (Düspohl et al., 2012). Instead, the network structure is co-developed with stakeholders and information from literature (steps 1 and 2). Subsequently, the discrete classes must be defined (step 3). Lastly, root nodes representing observations, modeled output, scenarios or potential actions are defined through unconditional probability tables, while child nodes are characterized by conditional probability tables . From appropriate input data sources and relationships, both have to be developed (steps 2 and 3).

2.3. Knowledge sources

Regarding the roadmap, (co)setup and application of the Bayesian Network was embedded in a participatory process with local stakeholders. Their knowledge was integrated in steps 1, 2 and 5 of our participatory research process (Fig. 1). It was elicited during individual interviews and two stakeholder workshops with scientific presentations, guided discussions and break-out groups (Table 1). Local stakeholders came from Tunisia, Algeria and Morocco, because of the similar nature of conditions and problems in the coastal regions of these neighboring countries.

Data from a multi-model ensemble was used to inform the setup in step 2 (input data). In addition, literature research supported steps 1 (framing) and 2 (input data). See the respective step descriptions for the details of the necessary knowledge and its integration.

2.4. Perception graphs

During the participatory process, individual perception graphs – a type of causal network or influence diagram – served to elicit and visualize the problem perspective of stakeholders (Döll et al., 2013). The perception graph is a directed acyclic graph containing the organization's goals, factors that influence the goals and possible or currently applied actions of the organization that affect these factors (i.e. adaptation measures to climate change in the water sector), with causal links between them (Döll et al., 2013). The aim of the perception graph is to describe the current system with causes and effects of climate change hazards on water in the country from the perspective of the stakeholder's organization. The causal network contains all relevant components of the system, their causal relationships and (in)dependencies (Sperotto et al., 2017), thus increasing system understanding and identification of key risks by considering all perception graphs. The perception graph was drawn by the scientist on a large piece of paper on a table while asking the stakeholder guiding questions. Once the structure and the links of the perception graph were defined, it was noted how factors and actions are expected to change in the future.

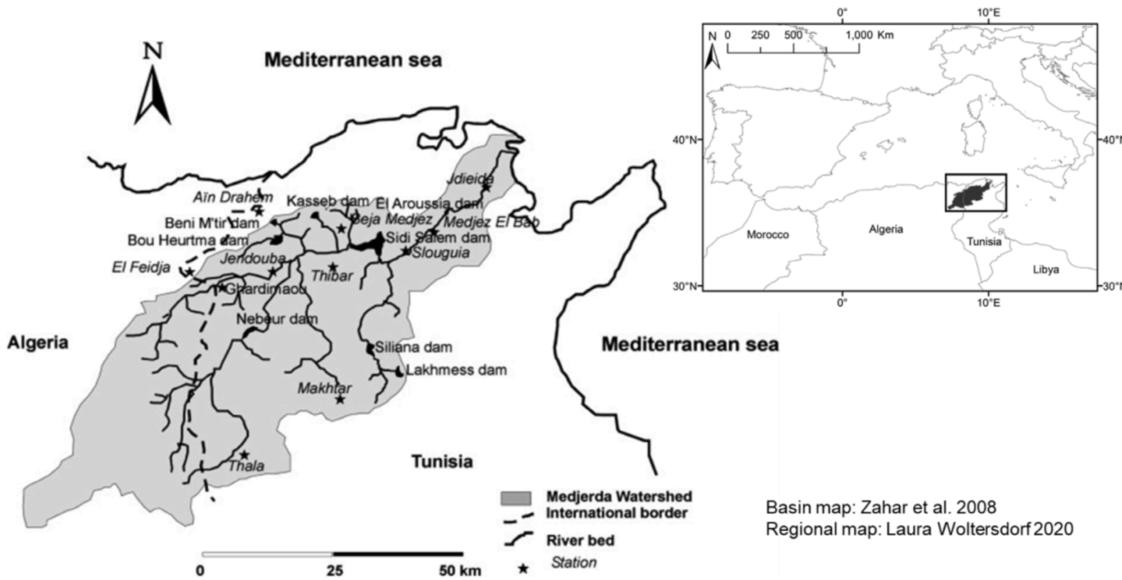


Fig. 2. Case study region Medjerda river basin in northern Algeria and northern Tunisia. Basin map adapted from Zahar et al. (2008).

3. Setup of Bayesian Network model

For each step (blue numbers in Fig. 1), first a brief description of the sequence of activities is given. The specific outcomes for the case study are then presented to support clarity of practise.

3.1. Step 1: Co-defining the real-world problem

Defining the real-world problem includes co-defining (i) the Bayesian Network model objective, (ii) the key risks, and (iii) the structure of the system to be modeled including its spatial and temporal extents and resolution. We defined the real-world problem regarding climate change hazards on water jointly in a process with stakeholders and project scientists during interviews and two workshops (Table 1) and from literature. To this end, individual semi-structured interviews were conducted with 13 water stakeholders concerned with climate change in Tunis (Tunisia, 4), Algiers (Algeria, 2) and Marrakech, Beni Mellal and Casablanca (Morocco, 7). They were selected based on stakeholder analysis and personal experience of a project scientist with long term research experience in the Maghreb. Each organization's perception of key risks and real world problems, time horizons of their work and data availability were elicited (see Table 1 for topic details). Interviewed stakeholders were based in national meteorological services, ministries concerned with water, national water supply agencies, basin agencies, universities, agricultural services and an intergovernmental organization. Based on interviews and literature, a qualitative and quantitative assessment was conducted to characterize the system under consideration. This served to streamline problem framing with the stakeholders but also to summarize those aspects potentially relevant for the subsequent network. For the case study area, it is given in the supplemental material. In addition, as part of the stakeholder interview, project scientists guided the stakeholder through the creation of individual perception graphs to elicit their problem perspective (including the organization's goals, influencing factors, and actions of the organization that affect these factors; see Section 2.4). The scientists analyzed the perception graphs using the software DANA (http://dana.actoranalysis.com/) (Bots, 2007), which allows to compare or combine the individual graphs, identify potential common factors, create digital versions for further discussions, and eventually shared some exemplary perception graphs in workshop I with all stakeholders. Subsequently during workshop I, the system's geographical and temporal boundaries were proposed by the project scientists and agreed upon with the stakeholders. Based on the bottom-up approach (Conway et al., 2019) of climate change assessments, the objective of the Bayesian Network model was merely narrowed down by project scientists to be a probabilistic quantification of key risks of climate change on water. Six stakeholders further met in break-out groups to determine such key risks, metrics to define them, and the data required. Based on this, project scientists proposed different options for two key risks and critical states for the two most important water sources in the Medjerda basin, i.e. one for groundwater and one for surface water, during workshop II. Different options comprising various degrees of complexity were presented by project scientists and discussed with local stakeholders before selecting the final risk indicators.

Regarding temporal and spatial boundaries, the Bayesian Network can be set up for any time horizon within the period of multi-model output, which was available until 2100. Most interview partners had time horizons for their work until 2020 or 2050; only the meteorological service used data until 2100. As a compromise between the shorter time horizons in water management and the longer time horizons in meteorology, we selected the period 2050–2079 as the evaluation period for our exemplary Bayesian Network model, and 1981–2010 as the currently recommended WMO reference period of long-term climate. The geographic system boundary of the Network was jointly determined to be the Medjerda river basin in Algeria and Tunisia (Fig. 2).

Stakeholder interviews showed that northern Tunisia and Algeria are already experiencing considerable water shortage. The impacts of climate change have already been perceived to be noticeable since the year 2000 and include more extreme precipitation events and more frequent droughts and floods. Both governments have responded to this with additional water supply infrastructure. Man-made reservoirs have already been exploited to the maximum now and will be strongly affected by climate change. In Tunisia and Algeria water from dams in the North is commonly transferred to regions with less water availability in the center of the countries. Envisioned strategies to mitigate water scarcity now and under worsening climate conditions in the future were non-conventional water resources (i.e. treated water reuse for agriculture) and improved water irrigation efficiency (e.g. drip irrigation). Water demand was expected to increase in the future because of population growth and more irrigation water need. Current data availability to stakeholders (also from climate models) differed greatly and depended on their domain of work. There was no local hydrological or water use model available for the Medjerda basin. Data from

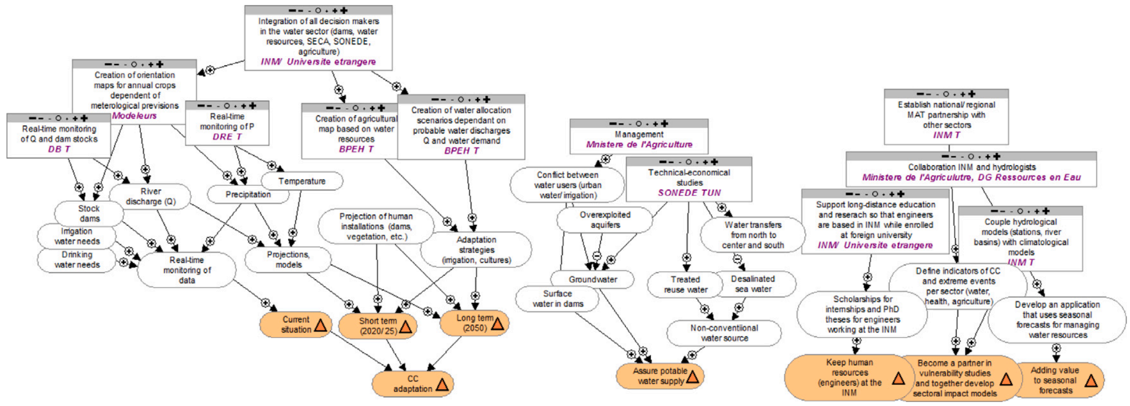


Fig. 3. Perception graphs of three stakeholders, depicting actions (rectangle), factors (oval, non-colored boxes) and goals (oval, colored boxes). Links are either positive (e.g. if "A" increases, "B" increases) or negative (e.g. if "A" increases, "B" decreases). For example regarding the organization on the left-hand side, performing increasingly the action "creation of water allocation scenarios" (rectangle) would lead to an increase of the factor "adaptation strategies" and an increased achievement of its goal of "climate change (CC) adaptation".

hydrological models have not been used so far for strategic planning including adaptation to climate change. Assuming that this situation is exemplary for many regions in developing countries around the world, this means that our approach of combining lower resolution global hydrological data available for all regions with local knowledge opens up new possibilities for supporting freshwater-related risk assessments in these imperiled regions.

At the end of the process, local stakeholders jointly decided the key risk addressed by the model to be the reduced ability to satisfy potable water and irrigation demands due to a climate change induced reduction of water resources. The reduction of water resources was further specified as reduction of groundwater and surface water resources, respectively. During workshop II, specific risk metrics were defined as "water-abstraction-to-resource" ratios (Section 3.2). Therefore, we defined the objective of the Bayesian Network model to provide a probabilistic estimate of the risk that climate change and water demand change pose for water supply from groundwater and from surface water by this ratio.

On the role of perception graphs

The role of the perception graphs was two-fold: (i) they structured the problem understanding and the definition of common goals in the stakeholder dialog by effectively showing where stakeholders are subtly talking about different things. And (ii) they, subsequently, served as the basis for the conceptualization of the Bayesian Network structure (Section 3.2.1). Regarding the latter, it may be attempted to integrate the individual perception graphs into one unified causal network which comprises the perspectives of all stakeholders in a joint system description (Düspohl and Döll, 2016) that could act as a direct candidate for the Bayesian Network structure. The software DANA, e.g., comprises a semi-automatic function for this purpose. Success may, however, differ depending on the level of complexity of the system at hand and on the level of similarity in the individual stakeholders' perception graphs.

For our study, three of the eleven created perception graphs are exemplarily shown in Fig. 3. They present very different perceptions of stakeholders regarding climate change impacts on water, depending on the stakeholders' organization. We found that integration into one unified causal network was not easily accomplished, as the perception graphs of each stakeholder did not have many factors and goals in common. This shows that during the interviews stakeholders reported about their specific perspective in detail, instead of generating a bigger picture that would make it easier to relate to the other causal networks. Still, the perception graphs were useful during the interviews in elucidating the perception of each stakeholder in a concrete way and visualize it. Consequently, we did not directly turn a unified causal network into the Bayesian Network structure but rather used the individual ones among other sources and principles to develop it (Section 3.2.1) taking also into account most important factors and relationships reported in literature. Moreover, the diverse views among stakeholders emphasize how important a participative process is, to embed the risk assessment in, in order to get all stakeholders on board.

3.2. Step 2: Co-developing the Bayesian Network model structure and acquiring input data

The Bayesian Network structure is the first of the three main components of the model (see Section 2.2). The Network structure was set up using the software Netica, and was co-developed as described in Section 3.2.1. As input for the Bayesian Network model (see also Fig. 1) we used data from a multi-model ensemble (Section 3.2.2) and data from literature and stakeholder knowledge (Section 3.2.3).

3.2.1. Bayesian Network structure

The Bayesian Network structure including nodes and links was co-developed based on

1. the IPCC (2014) concept of risks being composed of physical hazards, exposures and vulnerabilities,
2. the bottom-up approach (Conway et al., 2019) for climate change risk assessments starting from the decision-context, vulnerabilities and a well-defined objective defined as a critical threshold,
3. the stakeholder interviews and the perception graphs (Section 3.1),
4. a literature review of scientific publications addressing the region as well as Tunisian and Algerian national reports about freshwater resources and climate change,
5. local stakeholder input through break-out groups and discussions during workshops I and II (Table 1), and
6. the available output from the multi-model ensemble regarding the most important local water resources.

For development of the network structure, one or more risk nodes representing the identified key risks are generally the starting point. Depending on the formulation of the risk indicator, i.e. what function of which variables the risk indicator is, the immediately required variables to calculate the risk are placed above, e.g., pertaining to future water resources and future water demand; to these, further factors regarding hazards, exposures and vulnerabilities are added. Leading questions are: which potential climate-driven changes of hydrological variables from the multi-model ensemble are needed for the key risk calculation? Which non-climate change related changes of water resources and/or of water demand play a role? Which further, secondary factors may be

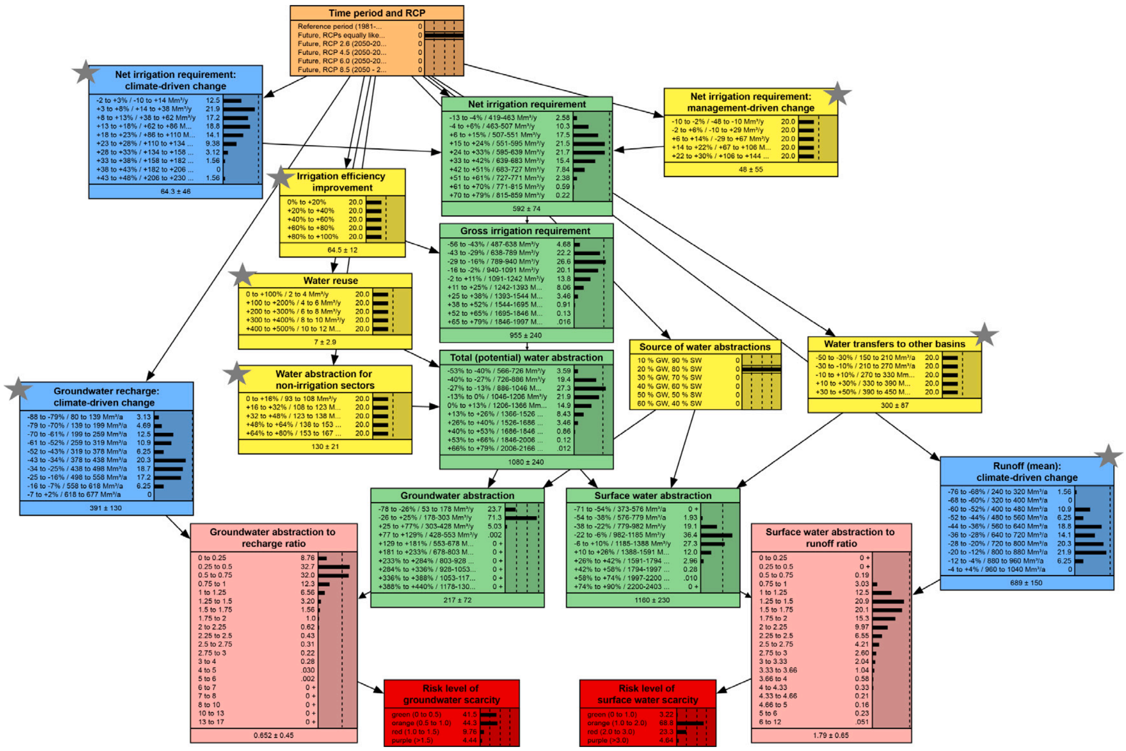


Fig. 4. Bayesian Network model with nodes and links. Each node shows the system variable name (top of nodes), classes and probabilities (middle section of nodes), and the mean value attained (bottom of nodes). Nodes represent: (1) selected RCP and future time period (orange box), (2) physical hazards (blue boxes, informed by multi-model ensemble), (3) exposures and vulnerabilities, (yellow boxes, developed from stakeholder knowledge and literature), (4) computed intermediate variables representing water use (green boxes), (5) key risks indicators (pink boxes) and qualitative risk levels (red boxes). CC denotes climate change. Stars denote the 'root nodes'.

impacting these? Do I need reference period information in addition to the changes?

The developed Bayesian Network model structure with variables and links is shown in Fig. 4. The setup of the classes seen in the figure is described later in step 4 (Section 3.3). For the model structure, various types of system variables reflect the IPCC concept of risks:

Two risk nodes are the focal point of the structure. They are placed at the bottom of the net (red boxes) and were defined for groundwater and for surface water as "risk level of groundwater scarcity" and "risk level of surface water scarcity", respectively. The qualitative risk level nodes depend on quantitative risk indicator nodes (pink boxes) of groundwater and surface water scarcity, respectively. The groundwater scarcity indicator is computed as the ratio of annual groundwater abstractions (under long-term mean annual climate) to long-term mean annual groundwater recharge. The surface water scarcity indicator is computed as the ratio of surface water abstractions (under long-term mean annual climate) to long-term mean runoff. Given the high uncertainties of runoff and groundwater recharge estimates for the Medjerda basin in the reference period, and to keep the complexity of the Network low, we assumed that mean annual surface water availability is equal to mean annual runoff and did not take into account that this may be reduced because of a decrease of groundwater discharge that is caused by groundwater use. The qualitative red risk nodes summarize the indicator nodes into threshold-based risk levels from stakeholder input.

Both risk indicator nodes are child nodes of nodes representing physical hazards (blue boxes) as well as vulnerabilities and exposures (yellow and green boxes). The three hazard nodes are: climate-driven change of net irrigation requirement, groundwater recharge, and runoff, respectively. Physical hazards are informed by the multi-model ensemble (Section 3.2.2). The water use-related vulnerability and exposure nodes are subdivided: the yellow nodes represent those which require input from stakeholders (root nodes and a water allocation decision node, see below), while the green ones are child nodes computed by the Bayesian Network model. The yellow nodes represent non-climate-driven, i.e. management-driven factors. All nodes are probabilistic type nodes, except for two decision type nodes : "Time period and RCP" (a selector box at the top of the net) and "Source of water abstractions", which need to be set by the user to select results for the specific time period and RCP, as well as a specific ratio of groundwater to surface water use while exploring climate scenarios and/or what-if cases.

We chose to insert the "Time period and RCP" node at the top as an implementation to enable the selection and analyses of various greenhouse gas emissions scenarios and time periods in an LCCRA. However, this design means that, technically, the selector node becomes the root node of all existing branches in the network (see Section 3.3.2). Despite this, we keep the nomenclature and continue to refer to those nodes at the beginning of their branch of physical hazards (blue) and exposures/vulnerabilities (yellow) as root nodes. For the sake of clarity, these are marked with a star in the figure.

The formulation of the risk indicator inherently defines what kind of input data is necessary for its calculation. In our case, because of the ratios, we required full values (i.e., as opposed to only changes) of water availabilities and abstractions. This may differ for other LCCRA cases. We used global multi-model ensemble output. Due to their global nature, process details on smaller spatial scales are lacking or vary, and large inter-model differences exist regarding the full values themselves, while, nonetheless, their projected relative changes are considered quite robust. This also proved to be true during the evaluation of our multi-model ensemble data with observational data for the historical time period of the 20th century . Therefore, we used the relative changes of the multi-model ensemble and local knowledge of reference values from literature to inform our Bayesian Network model with projections of actual values. In the nodes' classes in Fig. 4 we denote both – the range of the percentage change and of the full value – for the sake of clarity.

3.2.2. Input data: multi-model ensemble output

Our global-scale multi-model ensemble provided data for climate change hazards related to water including projected uncertainty (Fig. 1). We used the bias-adjusted outputs of four General Circulation Models (GFDL-ESM2M, IPSL-CM5A-LR, MICROC-ESM-CHEM and HadGEM2-ES), provided as part of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) for the period 1901–2099 to force three Global Hydrological Models: WaterGAP2.2d (Döll et al., 2003; Müller Schmied et al., 2021), LPJmL (Schaphoff et al., 2018), and CWatM (Burek et al., 2020). To take into account the uncertainty regarding future greenhouse gas emissions, four scenarios – the Representative Concentration Pathways RCP 2.6, 4.5, 6.0 and 8.5 – were included in the study. Output was consistently provided with a spatial resolution of 0.5° latitude by 0.5° longitude for all cells on the WATCH-CRU land mask, taking into account the DDM30 map of lateral drainage within river basins. In the Global Hydrological Model runs, socio-economic conditions including the extent and location of irrigated areas, were fixed to 2005 levels. The case study area covers eleven 0.5° grid cells. The Global Hydrological Model LPJmL, which is able to simulate the response of vegetation and thus evapotranspiration to increasing atmospheric CO_2 concentration and climate change, contributed two variants to the ensemble. In variant 1, future CO_2 concentrations are assumed to remain at the 2005 level, mimicking simulations of Global Hydrological Models such as WaterGAP and CWatM that cannot simulate vegetation response, while in variant 2, future CO_2 concentrations increase according to the RCP. For each of the four RCPs, 16 GCM-GHM model combinations (i.e. ensemble members) were considered in our study. Lastly, instead of creating one's own GHM model runs, freely accessible ensemble output of hydrological variables is available, e.g. from ISIMIP (www.isimip.org) or CO-MICC (www.co-micc.eu).

For the risk assessment in the Bayesian Network, the climate change hazard was defined as the relative change of three hydrological variables between the 30-year reference period 1981–2010 and the future period 2050–2079: (1) diffuse groundwater recharge, which is the water that percolates through the soil into the groundwater, (2) runoff under naturalized conditions, which is the part of the precipitation that is neither evapotranspired nor stored, and (3) net irrigation requirement, which is the fraction of the water abstractions for irrigation that would evapotranspire on a unit irrigated area assuming an unlimited water supply. The product of net irrigation requirement and a water use efficiency is the gross irrigation requirement, or the amount of water that must be abstracted to enable optimal crop growth. Water use efficiency can be increased by water management, and thus belongs to the yellow node category.

To obtain the hazard data, the GHM output of monthly data time series for these variables and for each of the ensemble members, respectively, was spatially aggregated over the 11 basin cells to obtain values for the entire basin, converted to annual time series, and the relative change computed between the reference and future time periods. The processing steps are given in Table 2. Thus, the global multi-model ensemble output provided projections of relative changes of these three variables for the time period assessed in the Bayesian Network model. The output was collected in a table per variable, consisting of the 64 values of relative change from each ensemble member — given in 4 rows (4 RCPs) with 16 values per row (16 GCM-GHM model combinations).

In addition, using the global models offers the additional advantage of providing a range of uncertainty in the hydrological projections. This would not have been possible using just one Regional Hydrological Model. In principle, the Bayesian Network could be informed by the output of a Regional Hydrological Model at the basin scale, however, in that case it will not be possible to capture the uncertainties associated with how individual hydrological models translate the climate change signal into hydrological changes of, e.g., total runoff, groundwater recharge and net irrigation requirement. Obviously, without using a multi-model ensemble, the Bayesian Network cannot produce a probabilistic distribution for its nodes representing water resources. And while a Regional Hydrological Model may be potentially more accurate, one may not be available in many regions worldwide requiring a risk assessment.

Table 2
Processing steps for the extracted multi-model-ensemble output to obtain the required relative changes of the three hazard-related variables in the Bayesian Network.

Analysis		Multi-model output typically consists of NetCDF files. Separate data files with individual time periods may have to be merged to yield the complete time series in question. For our three hazard variables, the corresponding hydrological model short names were 'pirruse' (potential irrigation use), 'qbwp' (blue water production), and 'qr_nat' (groundwater recharge under naturalized conditions). A time series of data was extracted for each ensemble member, i.e. model combination. The following processing steps were performed for each ensemble member separately.
Steps	1.	Monthly data extracted from NetCDF files for all grid cells within the basin (11 grid cells).
	2.	Units converted from provided $kg\,m^{-2}\,s^{-1}$ (= mm/s per square meter, i.e. a 'height of water column') to the water volume (m^3/month) using the land area of the grid cells.
	3.	For each month, all basin cells summed, yielding the monthly time series for the whole basin.
	4.	Annual average computed from monthly data, resulting in annual time series for the whole basin.
	5.	For each ensemble member and for the reference and future period separately, the periods' averages computed and converted to the specific units in the BN (Mm^3/yr)
	6.	Relative change computed between future and reference period.

Table 3
Local-scale information to quantify root nodes representing physical hazard variables: value for reference period based on literature for the Medjerda river basin (only Tunisian side).

Node	Value from literature	Source
Runoff	1000 Mm^3/yr	Hermassi (2014) value for Tunisian side of Medjerda basin
Groundwater recharge per year (deep and shallow)	664 Mm^3/yr	Ministère de l'Environnement et du Développement Durable (2009), value for Northern Tunisia
Net irrigation requirement	480 Mm^3/yr	Own calculation based on Institut National de la Statistique Tunisie 2018, Bouraoui et al. (2005), Ben Nouna et al. (2014), value for Tunisian side of Medjerda basin

3.2.3. Input data: literature and stakeholder knowledge

Input of the water supply risk Bayesian Network encompassed data on water resources, water demand and management in the study area during the reference period. A literature review and knowledge of local stakeholders served to provide values of all Bayesian Network variables for the reference period, as these are required to compute the two selected key risk ratio indicators from the projected changes. In addition, published expectations of change for management and water demand nodes were reviewed as the basis for plausible ranges of change in the designed scenarios.

Values for the reference period for the Medjerda basin as reported by literature are shown for root nodes impacted (starred blue nodes) and not impacted (starred yellow nodes) by climate change, in Tables 3 and 4, left-hand side, respectively. Regarding relative future changes

Table 4
Local-scale information to quantify root nodes representing exposure and vulnerability variables: [Left] values for the reference period based on literature for the Medjerda river basin (only Tunisian side), and [right] estimates of relative changes for the future period based on listed sources.

Node	Reference period		Future period		
	Value	Source	Probability range of relative change	Comment or assumption	Source
Net irrigation requirement: management-driven change	480 Mm^3/yr	Own calculation based on Institut National de la Statistique Tunisie (2018), Bouraoui et al. (2005), Ben Nouna et al. (2014)	−10% to +30%	Considering irrigation area, water efficient crops. No data found for NIR, only estimates for GIR for northern Tunisia available	Ministère de l'Environnement et du Développement Durable (2009)
Irrigation efficiency (consumptive use to abstraction ratio)	0.43	Ben Nouna et al. (2014)	0% to +100%	An increase by 100% results in a extremely high irrigation efficiency of 0.86	reasoning
Water reuse	2 Mm^3/yr	Chenini et al. (2003), ONAS (2019)	0% to +500%	Bahri (2001) estimate a 5% water reuse growth rate per year in Tunisia, without specification of time span. This would mean +2000% until 2065. We believe that a 500% increase of capacity to 12 Mm^3/yr might be a more realistic maximum increase as it is unsure if a continued growth of that magnitude will be sustained for such a long time in the future.	Bahri (2001)
Water abstraction for non-irrigation sectors	93 Mm^3/yr	Chenini et al. (2003), Hermassi et al. (2014) and own estimation based on reasoning	0% to +80%	Chenini et al. (2003) indicate a 13% growth rate of water demand of other sectors in Tunisia until 2030. Assuming linear growth demand until 2065 this would mean an increase of +40%. We chose a range until +80% to allow for what-if considerations under an even higher water demand than estimated.	Chenini et al. (2003)
Source of water abstractions	20% GW, 80% SW	Estimation based on stakeholder interviews	10% GW, 90% SW to 60% GW, 40% SW	Possible realistic range	Stakeholder interviews and reasoning
Water transfers to other basins	300 Mm^3/yr	Ministère de l'Environnement et du Développement Durable (2009)	−25% to +50%	The max. capacity of the Cap Bon canal is 470 Mm^3/yr (SONEDE, 2019)	Stakeholder interviews

for the latter, i.e. the management scenario root nodes, we estimated a range of possible future changes. See Table 4, right-hand side, for an overview with sources and assumptions.

3.3. Step 3: Setting up the Bayesian Network model

Final set up of the Bayesian Network model requires information for each node that in part needs to be pre-calculated before entering in the Network. The setup process is summarized in Fig. 5. It comprises the two remaining main components (see Section 2.2): (i) defining the distinct classes of each node and (ii) entering the probability distribution either directly in the form of unconditional probability tables (for the root nodes) or – where it depends on the parent nodes – in the form of conditional probability tables (CPTs, for child nodes).

As shown on the left-hand side of Fig. 5, setup is based on (1) the structure with variable titles, types of nodes and causal links implemented in Netica. In our multi-model-input-driven network, all but two nodes are probabilistic type nodes. Selector and Source allocation nodes are examples of potential decision-type nodes. (2) the tables of multi-model ensemble input, in our case in the form of 64 relative change values per variable. (3) the information from stakeholders and literature on (full) values in the reference period for all root nodes (hazard and management, blue and yellow starred, respectively). And, (4) the determined future management scenarios regarding possible ranges of change.

In a first step, the relations between a child node and its parent nodes are quantitatively defined for all child nodes in algebraic equations (Table 5). These relations are needed in two places: in the pre-processing when child class boundaries are derived from the boundaries of all its parents, but also in Netica when automatically generating CPTs of child nodes. CPTs can be elicited and entered manually, but if an algebraic relationship exists, they can be computed automatically.

Next, the calculation of classes and unconditional probability tables is described in Section 3.3.1, including the transfer to Netica, comments on fine-tuning the risk nodes and on parameter checks, while the generation of conditional probability tables is described in Section 3.3.2.

3.3.1. Pre-processing with MATLAB: computation of class boundaries, child node reference period full values and root node probability distributions

The range of the static classes should optimally only reflect the occurring range of values for the respective variable over all dynamically

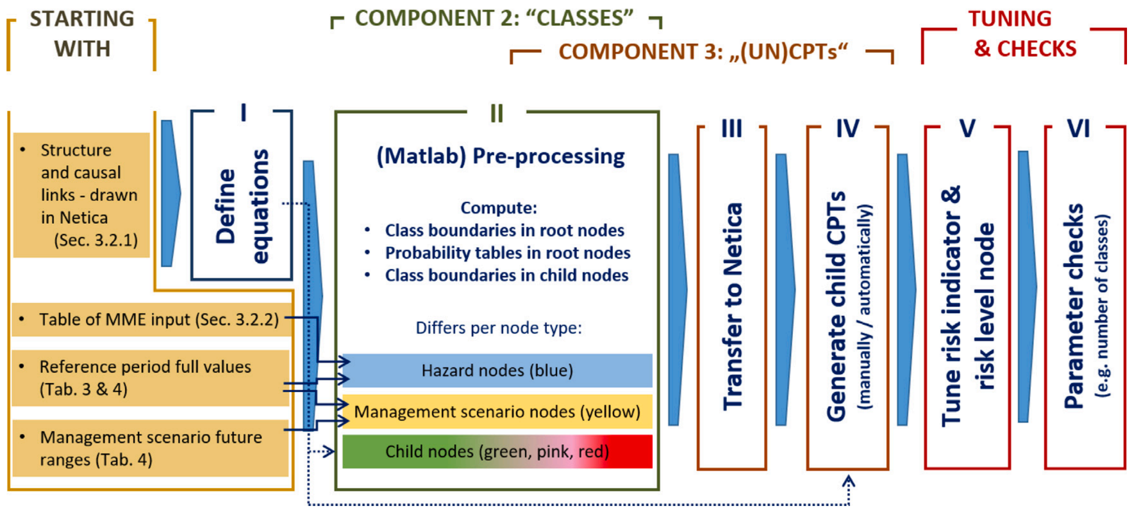


Fig. 5. Setup procedure of the second and third main components of the Bayesian Network model: defining the distinct classes of each node and generating the probability information either in the form of unconditional or conditional probability tables (CPTs).

Table 5
Equations to compute the conditional probability table of the child nodes in Netica (all variable node types are continuous and nature). Abbreviations not explained in the table are: ΔNIRc - Net irrigation requirement: climate-driven change, ΔNIRm - Net irrigation requirement: management-driven change, $NIR_{ref\ period}$ - Net irrigation requirement: reference period value, Ieff - Irrigation efficiency, in %, AbsO - Water abstractions for non-irrigation sectors, Reuse - Water reuse, Alloc - Source of water abstraction, i.e. groundwater abstractions as a fraction of total abstractions, in %, Trans - Water transfers to other basins, GWR - Groundwater recharge, R - Runoff (mean).

Child node title	Name	Equation
Net irrigation requirement (Mm^3/yr)	NIRt	$\mathrm{NIRt}(\Delta\mathrm{NIRc}, \Delta\mathrm{NIRm}) = (\Delta\mathrm{NIRc} + \Delta\mathrm{NIRm}) + \mathrm{NIR}_{ref\ \ period}$
Gross irrigation requirement (Mm^3/yr)	GIR	$\mathrm{GIR}(\mathrm{NIRt}, Ieff) = \mathrm{NIRt}/(\frac{\mathrm{Ieff}}{100})$
Total (potential) water abstraction (Mm^3/yr)	AbsT	$\mathrm{AbsT}(\mathrm{GIR}, \mathrm{AbsO}, \mathrm{Reuse}) = \mathrm{GIR} + \mathrm{AbsO} - \mathrm{Reuse}$
Groundwater abstraction (Mm^3/yr)	GWabs	$\mathrm{GWabs}(\mathrm{AbsT}, \mathrm{Alloc}) = \mathrm{AbsT} \cdot (\frac{\mathrm{Alloc}}{100})$
Surface water abstraction (Mm^3/yr)	SWabs	$\mathrm{SWabs}(\mathrm{AbsT}, \mathrm{Alloc}, \mathrm{Trans}) = \mathrm{AbsT} \cdot (1 - \frac{\mathrm{Alloc}}{100}) + \mathrm{Trans}$
Groundwater abstraction to recharge ratio	GWratio	$\mathrm{GWratio}(\mathrm{GWabs}, \mathrm{GWR}) = \mathrm{GWabs}/\mathrm{GWR}$
Surface water abstraction to runoff ratio	SWratio	$\mathrm{SWratio}(\mathrm{SWabs}, \mathrm{R}) = \mathrm{SWabs}/\mathrm{R}$

selectable time periods and scenarios. Defining classes therefore comprises defining appropriate lower and upper class boundaries (range) and a class size. We defined this range for both root nodes and child nodes, either by the given input data or by the passed down, combined ranges of parent nodes, respectively. The required information and our process below differs slightly for the different types of nodes (blue, yellow, green, pink, red) in the network. For each node type, we selected an appropriate number of classes (blue: 10, yellow: 5, green: 10, pink: 20, red: 4) considering data availability and detail needed. In general, the more precise the knowledge, the more classes are suitable.

Standard Bayesian Network software such as Netica cannot extract information for defining classes of a root node from a given multi-model ensemble or other data source; nor is it able to calculate the optimal class boundaries of child nodes depending on the ranges of values in the parent nodes. Instead, Netica requires this information to be entered manually. Therefore, we used the software MATLAB for calculating the required input into Netica for the different node types. We computed each node in the network this way from "top to bottom", i.e. successively the next node with the computed class ranges of all its parents as the new basis for its computations:

Root nodes representing physical hazards (starred blue nodes in Fig. 4): Based on the value range given by the reference period value from literature and the multi-model ensemble of future relative change values, uniform class boundaries were calculated in the form of relative change and of full value ranges for input into Netica (see blue boxes in Fig. 4). In addition, the probability distribution of changes in the variable was computed for each selectable climate scenario in the orange selector node in Fig. 4, i.e., for future periods the probability distribution was calculated for each individual RCP and for all RCPs mixed together. To this end, assuming that each ensemble member is equally likely, each output value of the 16 (individual RCP scenario) or 64 (all mixed scenario) multi-model ensemble members was assigned to its corresponding class and the probability for multi-model ensemble members to be in one class was calculated (e.g. 8 out of 64 ensemble members in one class represent a 12.5% probability). For the reference period the distribution was manually set to 100% in the class of zero change. A resulting probability distribution is exemplarily shown for groundwater recharge in Table 6.

Root nodes representing exposure/vulnerability (starred yellow nodes in Fig. 4): Based on the (full) reference period value and respective scenario ranges of relative change (Table 4), class boundaries were calculated in the form of relative changes and of full values as well.

Child nodes (green nodes in Fig. 4): Based on the minimum and maximum class boundary and the full reference value of each parent node and the quantitative relationship between the parent nodes (see Table 5), the child node's reference value for the reference period and the class boundaries were calculated.

Risk indicator nodes (pink): As for other child nodes, class boundaries and reference values were calculated. In addition, the uniform class boundaries over the range of occurring values obtained by MATLAB were manually adjusted to reflect details around actual critical thresholds after assessing the occurring values in iterations between analysis with the final Network and the Matlab processing routine (see "V" in Fig. 5). Adjustment included the number of classes and non-uniform class sizes.

Risk (level) nodes (red): For the actual risk node, a meaningful aggregation of the risk indicator classes was performed, to enable

Table 6
Exemplary probability distribution [%] of node "groundwater recharge: climate-driven changes" (percent probability rounded to one decimal digit, rows add up to 100% probability).

	Classes									
	−88 to −79%	−79 to −70%	−70 to −61%	−61 to −52%	−52 to −43%	−43 to −34%	−34 to −25%	−25 to −16%	−16 to −7%	−7 to +2%
Reference period	0	0	0	0	0	0	0	0	0	100
RCPs equally likely	3.2	4.7	12.5	10.9	6.3	20.3	18.8	17.2	6.3	0
RCP2.6	0	6.3	6.3	0	12.5	18.8	12.5	18.8	25	0
RCP4.5	0	6.3	12.5	18.8	0	25	18.8	18.8	0	0
RCP6.0	0	0	25	0	12.5	18.8	12.5	31.3	0	0
RCP8.5	12.5	6.3	6.3	25	0	18.8	31.3	0	0	0

effective risk management and decision-making. Four classes (green, orange, pink, red) reflected the user's specific view of the actual thresholds between acceptable and unacceptable performance; the assigned thresholds defined the class boundaries.

When transferring the class values into the nodes in Netica, the (full) values of e.g. net irrigation requirement (in Mm^3/yr) and not the relative (in percent) were entered into Netica[4] and used further to calculate the full values down the graph. To aid analysis, the class titles in the nodes of the Bayesian Network also showed the relative changes (%), as computed above, in addition to the full value ranges ($Mm^3/year$).

The computed full values for child node variables in the reference period are given in Table 7. These were necessary in the process to generate the relative change class ranges in addition to the full value classes, and as potential quality checks (see below for "VI" and Section 3.3.3). The computed class boundaries – both in the form of relative change and (full) value ranges – are shown in Fig. 4. They were determined to capture all possible future values.

The classification for the risk levels (red nodes) is shown in Table 8. We defined the thresholds for the levels differently between surface water and groundwater scarcity, choosing higher abstraction to runoff/recharge ratios for surface water risk levels for two reasons: (i) dams can store surface water even over several years, allowing to use the otherwise transient resource more fully, i.e. closer to 100%, without actually being in unsustainable water use scenarios, and (ii) taking into account that because of return flows, accumulated total abstractions along the river may sum up to beyond 100% of the available runoff. In general, these thresholds must be adapted individually to the system at question by the expert using the Bayesian Network according to their needs. If necessary, these thresholds should be determined in a participative process with stakeholders of the particular system at hand.

The optimal number of classes in each node may vary and should be carefully checked (see "VI" in Fig. 5). We found that the multi-model-input-driven, quantitative nature of the Bayesian Network required a higher number of classes than more traditional Bayesian Networks, which are kept as simple as possible to improve decision-making. However, broader classes may lead to bias in average values in the Netica interface (at bottom of nodes), e.g. especially visible as deviations in the reference period mean, where exact values from pre-processing exist (Table 7), because of the size choice of class ranges and the position of the exact value within it (i.e., if not chosen in such a way that the reference value of 0% change sits in the middle of a class). For a chosen class, Netica uses simply the class average in a weighted mean with the probabilities to calculate the node mean at the bottom of the box. Naturally, the higher the number of classes, the smaller the range for a value in it, the smaller the magnitude of deviations. The deviations worsened for increased class sizes (i.e., reduced number of classes for the given range). Therefore, the quantitative model data requires more classes to reflect the correct mean reference value in the Netica software

Table 7
(Full) values of child nodes for the reference period (1981–2010) computed with MATLAB.

Child node name	Result
Gross irrigation requirement	1.116 Mm^3/yr
Total (potential) water abstraction	1.207 Mm^3/yr
Groundwater abstraction	241 Mm^3/yr
Surface water abstraction	1.266 Mm^3/yr
Groundwater abstraction to recharge ratio	0.36
Surface water abstraction to runoff ratio	1.27

interface and yield optimized precision in the mean future values. However, the class sizes have become too finely resolved if 'holes' in the probability distribution become pronounced, and the number of classes should be reduced. Tests with varying numbers of classes allow an optimal choice in the system at hand. In our case, having more than 10 classes for a child node was not feasible because of the limited overall number of ensemble members in the input data to produce smooth probability distributions. In addition, more classes make it harder for the stakeholders to understand the result of the Bayesian Network. This to some extent differentiates the more quantitative Bayesian Network from more qualitative ones, and the higher number of classes suitable for multi-model-driven nodes highlights the need for introducing the reduced (four) risk levels in the final red node.

3.3.2. Unconditional probability distributions of root nodes entered and conditional probability tables of child nodes generated in Netica

The MATLAB results for probability distributions of blue root nodes (Fig. 4, marked by stars) was then transferred into the respective node in Netica: Normally, they would be entered in an unconditional probability table, since root nodes do not have any parents that they depend upon. However, in the design with a selector node (see Section 3.2.1), technically, the selector node becomes the root node, i.e. the parent node to all starred nodes. Subsequently, the values of the probability distribution are entered in the conditional probability table of the node instead, in the respective row of the selectable scenario of the parent. The output structure of the pre-processing in the example (Table 6) is chosen to mirror the CPT table in the node in Netica.[5]

For the yellow root nodes, a probability distribution of changes in the future is entered manually that represents equally-likely probabilities over all their classes by default, except for the reference period which is set to 100% in the class of zero change (Table 9). By selecting a class in the node manually during simulations, the state can be alternatively set "deterministically" to one of its classes (i.e., representing a state in the future with a probability of 100% to be in that class range of values), allowing exploration of different scenarios, depending on the respective anticipated certainty and magnitude of the management factor in an LCCRA.

For the aggregation in the red risk level nodes, nodes in Netica are set to "Nature" and "Discrete", the table is set to "Deterministic" and

[4] For probabilistic type nodes, nodes set to "Nature" and "Continuous", then entered under "Discretization". For the two decision type nodes, nodes set to "Decision" and "Discrete", then only class titles but no numeric class boundaries need to be entered under "State names".

[5] For all probability nodes, the table in Netica is set to "Chance" and "% Probability".

Table 8
Classification of risk levels for groundwater and surface water according to their abstraction to recharge ratio.

Risk level	Groundwater scarcity	Surface water scarcity	Explanation
Green	0 to 0.5	0 to 1	Maximum abstractions equal recharge, no problem.
Orange	0.5 to 1	1 to 2	Approaching over-use, start considering actions.
Red	1 to 1.5	2 to 5	Not sustainable anymore, feasible only for a certain period if actions are taken afterwards.
Purple	>1.5	>3	Cannot cope with this situation after a few years.

Table 9
Exemplary probability distribution [%] of node "Net irrigation requirement: management-driven change". Class notation in the Network is converted to full values based on the reference period value.

	Classes in %-notation				
	−10 to −2%	−2 to +6%	+6 to +14%	+14 to +22%	+22 to +30%
Reference period	0	100	0	0	0
RCPs equally likely	20	20	20	20	20
RCP2.6	20	20	20	20	20
RCP4.5	20	20	20	20	20
RCP6.0	20	20	20	20	20
RCP8.5	20	20	20	20	20

"Function". Then, each (parent) risk indicator class can be assigned to one of the risk levels in the table, according to the thresholds defined in Table 8. Only the four state titles but no numeric class boundaries, i.e., state numbers need to be entered.

Lastly, the CPTs of all child nodes were generated. The CPTs are the basis for the Bayesian calculation of the probability distributions in the child nodes, including in the final risk indicator nodes. They can be entered manually, e.g. – generally – when the information has been elicited from experts or – in the case of the risk level nodes (red) – for the manual aggregation of risk indicator classes into the four risk levels. Where a relationship between nodes can be described by an algebraic expression (e.g. total water abstraction is the sum of gross irrigation requirement and abstraction for non-irrigation sectors, minus the reused water), Netica additionally allows to compute the CPTs automatically. We used this based on the defined equations in Table 5 for all green and pink child nodes. The Netica computation of the CPTs was based on 10^6 samples per cell.

3.3.3. Model evaluation

Before simulations with the Bayesian Network model can support an LCCRA, first a simulation of the system's child node variables and risk states in the reference period should be analyzed to ensure the model's ability to reflect the quantitative and qualitative assessment of the "current" state . To this end, a consistency check with literature for the reference period should be conducted.

Very few data are available to evaluate our model. Our value computed for the node "groundwater abstractions" during the reference period is in line with reported literature values. We computed total (potential) water abstraction to be 1207 Mm^3/yr, and assuming 20% to be abstracted from groundwater, groundwater abstraction of 241 Mm^3/yr is computed. Official Tunisian reports (Ministère de l'Agriculture, des Ressources Hydrauliques et de la Pêche, 2017) estimate abstractions from deep groundwater in Northern Tunisia to be 148 Mm^3/yr in 2006 (276 Mm^3/yr in 2015), with no information on shallow groundwater abstractions, thus, placing our value on the same order of magnitude and slightly larger than this literature value which is missing the shallow groundwater abstractions.

Regarding the node "groundwater abstractions to recharge ratio", we also found that our computed ratio (0.36) is in line with reported values. The Tunisian Water Ministry (Ministère de l'Agriculture, des Ressources Hydrauliques et de la Pêche, 2017) indicates that for the North of Tunisia the ratio of annual groundwater abstraction to deep groundwater recharge was 43% in 2006 (88% in 2015). This does not include illegal boreholes which, however, constitute only 5% of deep groundwater abstractions for the whole of Tunisia in 2011 (Ministère de l'Agriculture, des Ressources Hydrauliques et de la Pêche, 2017). Assuming that shallow groundwater is abstracted with the same ratio than deep groundwater, the reported 43% agree well with the computed 36%.

It was impossible to check the consistency for surface water results with literature because data on surface water abstractions is scarce and the reported dam storages do not show year to year abstractions (Ministère de l'Agriculture, des Ressources Hydrauliques et de la Pêche, 2017). Hermassi et al. (2014) report that 80% of water abstractions in the basin occur from surface water, which was used for the allocation ratio of surface water in the node "Source of water abstractions". The scarcity of data emphasizes the need for a tool like in this study to enable risk assessments in such regions even in the face of scarce data and uncertainty.

Validation of the changes projected by the Bayesian model is not as directly possible. No historic time series of observed groundwater resources and surface water resources exist, which would enable to check how past climate change (or variability) was translated into changes of water resources, and compare to the hydrological model results, and enable to validate the model. It is essential to appropriately select input data to reflect known constraints of the hazard projections, i.e. we only considered long-term annual changes in hydrologic variables in accordance with the capability/uncertainty of the global hydrological models.

4. Application of the Bayesian Network model

4.1. Step 4: Simulations and analysis with the Bayesian Network

An analysis of the future changes of the physical hazards, independent of the affected larger system, can already give insights into the expected future pressure on the joint system from the physical point of view (Section 4.1.1). To support an LCCRA, a suite of risk scenarios must be developed that combine potential changes of hazards with potential changes in vulnerabilities/exposures to assess future risks (Section 4.1.2). Here, a simulation of the reference state in the reference period must always be part of the scenario suite to serve as a baseline for the future scenarios in the risk assessment, i.e. it is possible that a risk already exists today (in the reference period), so that a climate change risk assessment is able to consider that only the difference to the baseline is the climate change related risk. Lastly, the impact of potential actions or policy measures, which are considered for mitigation or adaptation, can be explored through the Bayesian Network model (Section 4.1.3).

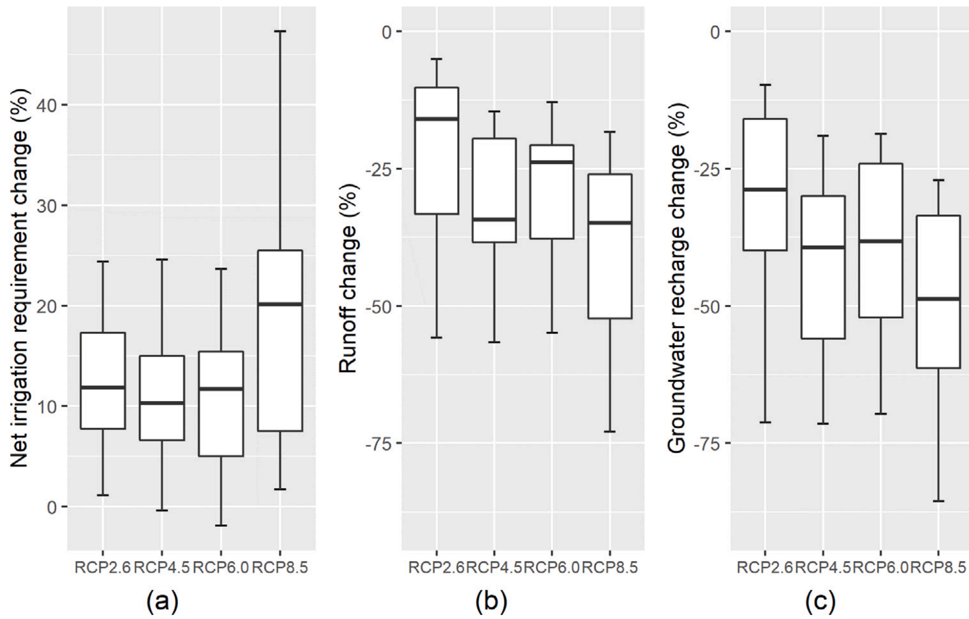


Fig. 6. Projected relative changes [%] of multi-model ensemble output per RCP between the periods 1981–2010 and 2050–2079 of (a) net irrigation requirement, (b) mean runoff and (c) groundwater recharge change.

Name	1 Ref_Ref	2 2.6_Ref	3 Equal_Ref	4 8.5_Ref	5 2.6_Best	6 Equal_Equal	7 8.5_Worst
Period	Reference	Future	Future	Future	Future	Future	Future
Climate	Reference (RCPs equally likely)	RCP 2.6	RCPs equally likely	RCP 8.5	RCP 2.6	RCPs equally likely	RCP 8.5
Water use	Reference	Reference	Reference	Reference	Best case	Equally likely	Worst case

Fig. 7. Scenarios generated in this study combining different scenarios of climate change between the reference period 1981–2010 and the future period 2050–2079 with scenarios of reference water use and of changing water use (naming scheme: climate_water use). “Scenario 1” is not an actual scenario but represents the conditions during the reference period.

4.1.1. *Future period changes in physical hazards*

Due to climate change, all 64 multi-model ensemble members projected a considerable decrease in runoff and groundwater recharge and an increase in net irrigation requirement (Fig. 6). These values are based on the obtained multi-model input (Section 3.2.2). Net irrigation requirement was projected to increase with respect to the median of all ensemble members by +12% (min. +1% to max. +24%) for RCP2.6 and by +20% (min. +2% to max. +47%) for RCP8.5. Runoff was projected to decrease with respect to the median by −19% (min. −56% to max. −5%) for RCP2.6 and by −31% (min. −73% to max. −18%) for RCP8.5. Median groundwater recharge was projected to decrease by −29% (min. −71% to max. −10%) for RCP2.6 and −49% (min. −86% to max. −27%) for RCP8.5. As expected, for all three physical hazards decreases (in groundwater recharge and runoff) and increases (in net irrigation requirement) were considerably higher for RCP8.5 compared to RCP2.6. While projected changes showed considerable uncertainty, even for RCP2.6 considerable changes compared to the reference period were shown to exist.

4.1.2. *Simulation of risk scenarios*

To explore potential futures, we created six different scenarios of RCPs and water use (Fig. 7). These should be developed in the participatory process to define and capture the required range for the problem assessment. The scenarios represent what-if cases, and in practise are obtained combining the respective RCP scenarios in the selector node with water use scenarios selected in the yellow root nodes. To this end, the states of the latter nodes were either set deterministically to one of its classes or left in a state where all classes remain equally likely. Scenarios 2–4 vary the climate scenario and keep the water use fixed at reference levels, while scenarios 5–7 build a series of best to worst cases including both climate and water use scenarios. The former would be a suitable approach to attribute the impact different RCPs have on the risks, even without considering worsening water use, while the latter is a basis to assess overall impacts in a potential LCCRA. The Bayesian Network model was then used to calculate probability distributions of the groundwater and surface water scarcity and thus the respective water supply risks for the future period 2050–2079 under these six risk scenarios. To establish the reference conditions, the Bayesian Network model was also used to determine the same risks during the reference period 1981–2010. Conditions during the reference period are by definition characterized by 0% change. Comparing the risks between the reference period and the future period for the six scenarios (2–7) enables to understand how risks for water supply may develop in case the different scenarios became true.

Results of probability distributions for all seven computed child nodes of the Bayesian Network are given in Figs. 8 and 9. For the reference period, computed groundwater abstraction to recharge ratio from pre-processing was 0.36, the surface water abstraction to runoff ratio was 1.27 (Table 7). Based on the risk level thresholds (Table 8), surface water scarcity was therefore already in the orange risk level, while groundwater scarcity was classified in the green risk level. This was reflected in the probability distribution of both risk level nodes in the baseline scenario (Ref_Ref in Figs. 9(a) and 9(b)).

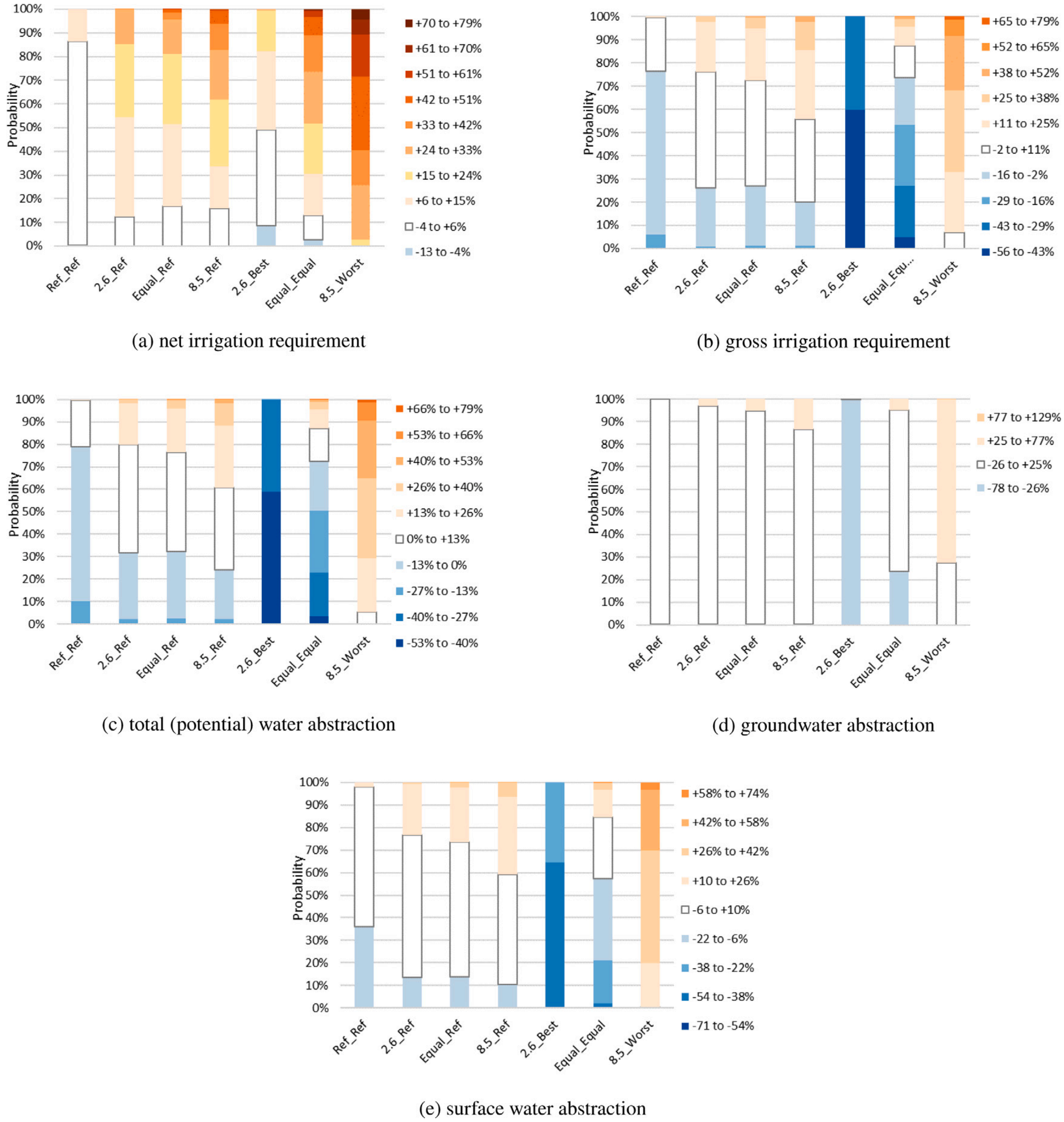


Fig. 8. Cumulative probability distributions of the computed child nodes: (a) net irrigation requirement, (b) gross irrigation requirement, (c) total (potential) water abstraction, (d) groundwater abstraction, (e) surface water abstraction for the seven scenarios (Fig. 7). The class including zero change is visually emphasized with a contour line.

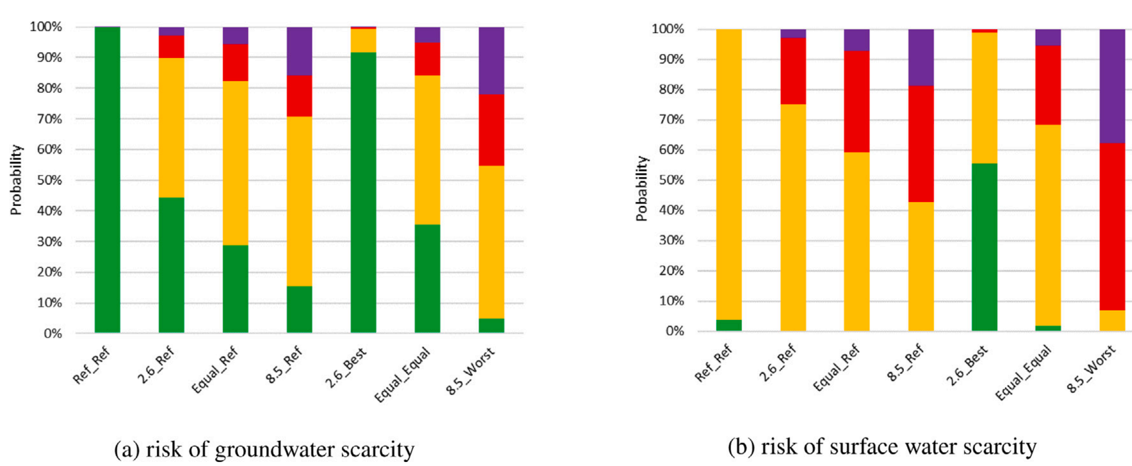


Fig. 9. Cumulative probability distributions of risk levels for the nodes (a) risk of groundwater scarcity and (b) risk of surface water scarcity, for the seven scenarios. Risk levels: green, yellow, red, purple (Table 8).

Results further show the change in the probability range for the future scenarios compared to the reference scenario for the seven computed nodes. Under worsening climate conditions with reference water use (2.6_Ref, Equal_Ref, 8.5_Ref), more water abstractions will be needed than in the reference period (Fig. 8). Consequently, the two risk indicators for water scarcity also show an increased probability for an orange, red and purple risk level. For example, under RCP2.6 and reference water use (2.6_Ref) the probability for the risk of groundwater scarcity (Fig. 9(a)) to be in the green level is 44%, in the orange 45%, in the red 7% and in the purple 3%. The situation considerably deteriorates if additional to worsening climate conditions the water demand also increases because of other reasons than climate. For instance, under RCP8.5 and the highest water use scenario (8.5_worst), the probability for the risk of groundwater scarcity to be in the green risk level is 5%, 50% in the orange, 23% in the red and 22% in the purple risk level.

The impact of climate individually can be seen, e.g., when comparing RCP2.6 and 8.5, both with reference water use (2.6_Ref, 8.5_Ref) in Fig. 9(a). For RCP2.6, the probability for the risk of groundwater scarcity to be in the green level is still 44%, which diminishes to only 15% under worsening climate conditions, even with no further pressure from growing water use. The impact of water use on top of the climate conditions is twofold: On the one hand, for RCP8.5, increasing reference water use to the worst case (8.5_Ref, 8.5_Worst), increases the cumulative probability to be in the two worst levels from 29% to then 45%. On the other hand, managing water use well into the future has the potential to alleviate the risk substantially, as can be seen comparing, for example, RCP2.6 with both reference water use and best case water use (2.6_Ref, 2.6_Best): compared to the current water use, in a best case management scenario and adaptation, the probability to be in the acceptable level (green), which was already diminished by climate conditions alone from 100% to 44%, can regain a probability of over 91%. Detailed attribution of factors is possible through more finely designed scenarios or assessing individual policy measures (Section 4.1.3).

4.1.3. Impact of action or policy measure

The Bayesian Network can be used to determine the impact of a certain action or policy measure on risk. The impact of policy measures leading to different increases of irrigation efficiency on the risk for surface water supply is shown in Fig. 10. If there is only a small irrigation efficiency increase (0 to +20%, Fig. 10(a)), the probability to be in the orange risk level for surface water supply is 50%, to be in the red is 40% and in the purple risk level 11%, with respect to the scenario of all RCPs being equally likely. With the highest irrigation efficiency change (+80% to +100%) the risk level for surface water supply is reduced, with a probability of 9% to be in the green, 78% to be in the orange, 12% in the red and 1% in the purple risk level for the same scenario. In an LCCRA, proposed policy actions can then be strategically evaluated according to the needs, prioritized by effect or a portfolio of actions determined to meet specified goals of risk reduction.

4.2. Step 5: Evaluation of implemented measures

Climate change adaptation should be done in an adaptive and iterative risk management process (IPCC, 2014). Within this process, the impact of implemented adaptation measures should be monitored, thus leading to an improved knowledge about the system. The Bayesian Network can then be updated, also including changed input data or beliefs, e.g. by modifying conditional and unconditional probability tables. It then serves as an improved tool for a new round of the LCCRA process.

5. Experts' evaluation of using Bayesian Networks for local climate change risk assessments

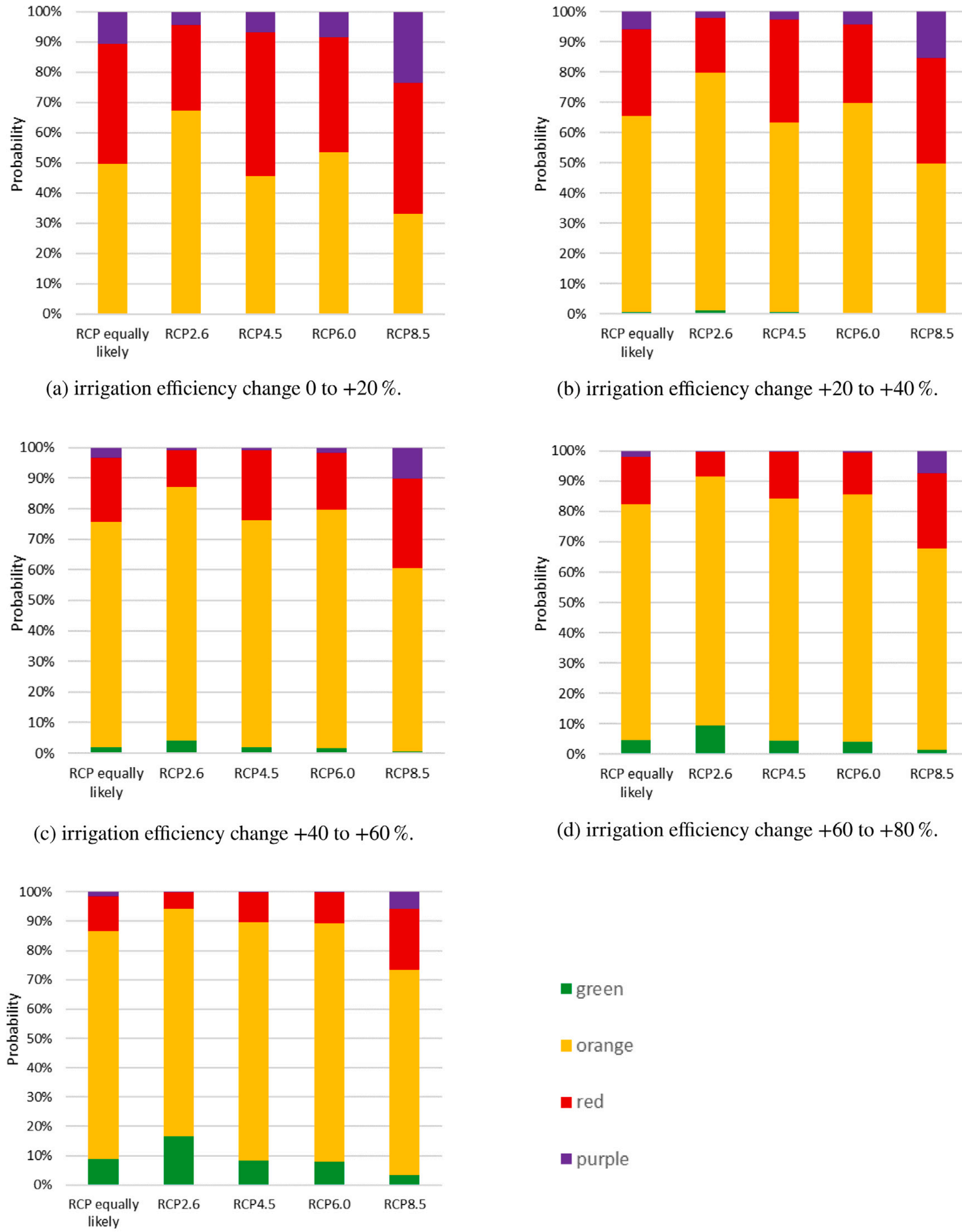
Local experts evaluated the use of Bayesian Networks for local climate change risk assessments largely positively (Fig. 11). Bayesian Networks were seen as a useful way to integrate experts' and stakeholder knowledge about climate change impacts on water. The usefulness of Bayesian Networks as a tool for local climate change risk management was evaluated rather differently among the experts, with one indecisive and one not so positive. While probabilistic computations for local risk assessments were evaluated very positively, the difficulty for stakeholders to think in terms of probabilities was simultaneously considered more problematic. Respondents thought it was rather important to think in terms of probabilities for this kind of management problems and half of the respondents could imagine to use Bayesian Networks for their daily work. The experts think that experts from engineering companies followed by experts from universities can use Bayesian Networks most easily, more easily than experts working in administration.

Regarding open question 1 "how should Bayesian Networks be adapted to be more useful, so local experts could better work with them?", respondents mentioned that it would be important to integrate local data into the Bayesian Network and to enable the comparison of model results to observation data for the reference period. In addition, capacities of local users to apply Bayesian Networks need to be strengthened through training with real data. Introducing a user-friendly interface with guiding elements how to use the Bayesian Network software, indicator explanations and manuals to the Bayesian Network software would facilitate comprehension, calculations and avoid misuse. They acknowledged that the Bayesian Network would also need to be adapted, and expressed the need to be able to integrate more qualitative data. Regarding open question 2 "who do you think is suited to use Bayesian Networks in your country?", respondents answered that water resource managers such as those in basin agencies or agricultural management agencies or a specific institute under the agricultural ministry, statisticians, researchers with specific training, high level managers, meteorologists (engineers and technicians) and researchers would have the necessary capabilities to work with the model. For open question 3 "in your daily work, for which concrete tasks or problems could you imagine that Bayesian Network could be useful?" respondents mentioned the support for risk management in a scientific and objective manner, decision-making for projections, planning and vulnerabilities for many different sectors such as for mid-term and long-term water management and planning, infrastructure for water mobilization and flood protection, irrigation management, water distribution and allocation among sectors, erosion management and dam protection. A meteorological service could use such a Bayesian Network in impact studies of climate change on water and agricultural production. For open question 4 "which difficulties or hindrances do you see for you working with Bayesian Networks/or colleagues in your organization?", respondents mentioned that the tool may be helpful for water resources management in their country. They stressed that Bayesian Network modeling requires availability of input data (e.g. hydrological data), interdisciplinary collaboration and an understanding of all the relations between factors (nodes). The multiple use cases and potential users collected here suggest that the method is promising in the context of freshwater-related risk assessments and adaptation planning in the face of climate change.

6. Discussion

6.1. Alternative Bayesian Network structures for integrating multi-model ensemble estimates

The co-developed Bayesian Network is in two aspects a rather atypical example — one, we used only quantitative and full values



(a) irrigation efficiency change 0 to +20 %.

(b) irrigation efficiency change +20 to +40 %.

(c) irrigation efficiency change +40 to +60 %.

(d) irrigation efficiency change +60 to +80 %.

(e) irrigation efficiency change +80 to +100 %.

Fig. 10. Impact of management actions on risk level: impact of a change in irrigation efficiency on the risk level for surface water supply in the period 2050–2079 for the six scenarios. The states of all other (yellow) management nodes were set to be equally likely except for the "source of water abstractions", which was set to 20% from groundwater.

throughout the network and, two, we did not use beliefs to elicit CPTs but instead all nodes are connected through algebraic equations of a physically quantifiable relationship. Thus, we transferred the deterministic physical relationships into the inherently probabilistic representation of the Bayesian network. This has several advantages, mainly the readily available graphical user interface, the inherent representation of uncertainty, the ease to explore scenarios by the user, and using the Bayesian Network tool simplified certain computations, e.g. the automated computation of child node CPTs by the (Netica) software. The main advantage, though still unexploited, is the gained ability regarding the ease of extension to integrate additional factors — also qualitative beliefs. The atypical character, however, was also a direct result of the formulated key risk and network structure that came from the stakeholders in the participatory process.

In the following, we will discuss briefly (i) the extension of the network with qualitative factors, and (ii) examples of alternative Bayesian networks and key risk formulations, that use information on climate change hazards as estimated by a multi-model ensemble.

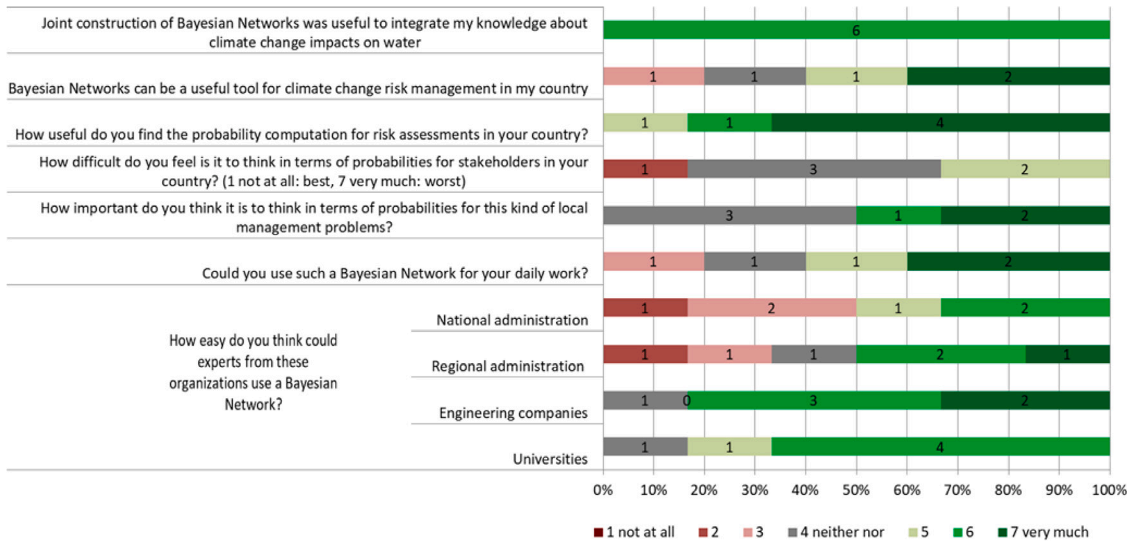


Fig. 11. Experts' evaluation of using the presented Bayesian Network for LCCRAs (Likert scale from 1: not at all (worst) to 7: very much (best)).

6.1.1. Qualitative factors

Qualitative factors are not yet reflected in the example network as this study focused on the integration of multi-model ensemble hazard estimates. Experts involved in the co-development of the Bayesian Network suggested improving the network by adding qualitative nodes to the quantitative ones, e.g., a node "farmers education" with the classes "high", "medium", "low" linked to the quantitative water use node "gross irrigation requirement" in Fig. 4. This would require converting the qualitative scale into a quantitative scale in order to link the qualitative and the quantitative nodes involved. Fig. 12(a) shows an example of such a translation node where the "irrigation reduction potential due to education", i.e. the "believed" quantitative impact must be obtained. Again, the CPT of the translation node must be set, which enables to capture the inherent uncertainty in the translation as well. Literature studies on the translated impact can be used if they exist. Commonly, the table will be elicited through (several) expert interviews. E.g., for "low" education, they rate the strength of their belief that the irrigation reduction is in the class of "0 to −10%", etc. The beliefs of several experts can be averaged or weighted by their elicited confidence in their beliefs.

6.1.2. Implications regarding the choice of the key risk indicator

The key risk indicator in our study that was suggested by the stakeholders as the abstraction-to-resources ratio required full values to be computed, and therefore a probability distribution over quantitative, full value classes in each parent node. There are many other suitable key risk indicators that do not require the probability distribution of full values. For example, key risk indicators may be defined as a function of only relative changes of certain relevant variables, as climate change often causes risks just because a system that is adapted to certain conditions is expected to suffer more from larger than from smaller changes. The example in Fig. 12(b) comprises a weighted addition of the changes of two variables to compute the risk indicator. In this case the relative changes provided by the multi-model ensemble and for the management scenarios would be sufficient, and differently to the key risk indicator in our study, it would not be necessary to know variable values for the reference period. Another alternative is a purely qualitative key risk indicator that is computed by combining multi-model based hazard changes with qualitative vulnerability classes through expert elicitation (see example in Fig. 12(c)). One main aspect that required the Matlab preprocessing was to compute quantitative class boundaries for each node from the occurring range of values. For non-quantitatively defined classes such as "low" and "high", obviously no such processing is required. However, with rising system complexity and number of nodes, the strain on experts for interview elicitation for the large number of CPTs should not be underestimated.

In summary, three classes of key risks exist with differing implications for the required pre-processing. (1) Qualitatively elicited risk indicators require only pre-processing of the multi-model ensemble data. (2) Quantitative risk indicators that are only a function of relative changes require, in addition, pre-processing for class boundaries. (3) Quantitative risk indicators that are a function of full values require the above, plus pre-processing with local reference period values.

6.1.3. Aspects regarding the different approaches to set CPTs

One of the main advantages of Bayesian Networks lies in their flexibility to define the relationship between nodes through CPTs, enabling integration of influences even in the face of varying degree of knowledge and certainty. If there is little knowledge about system factors, they can be classified qualitatively in a typical Bayesian "Belief" Network, where these relationships can be expressed via the elicited beliefs of experts (i.e. the tables allow to define the "believed" probability distribution for the given input combination of classes of the parent nodes). Thus, also factors that are not algebraically consistent can be related to each other. Similarly, another approach for completely qualitative networks assigns classes (e.g. low, medium, high) to a range of numbers (e.g. 0 to 1), to enable the use of algebraic equations in an attempt to more objectively quantify relationships. On the opposite side of the spectrum, if quantitative knowledge about system factors exists, is the possibility to use algebraic expressions for known (physical) relationships or derived from available data — with CPTs computed based on those, respectively.

While the latter requires quantitative knowledge to be available, it allows to explicitly consider two aspects separately: the combination of the effect of the parent nodes onto the child factor with their relative strengths in the relationship and the consequent evaluation in qualitative classes, i.e. what constitutes a low/high risk. Both former "belief" approaches allow networks when quantitative data on relationships are scarce, but their process blends the two aspects to a certain degree: in the first, when prescribing a probability distribution based on the parents' classes in the table, e.g. combining low, medium or high farmers education with low, medium or high climate-related rise in irrigation need to its meaning for low, medium or high risk for water scarcity, the experts belief must simultaneously incorporate both the relative strengths and where the critical thresholds within the system lie that will lead to a risk or not. In the second, similarly, it is critical that the formulated algebraic equation represents both aspects simultaneously for a sensible model of the relationship. Without

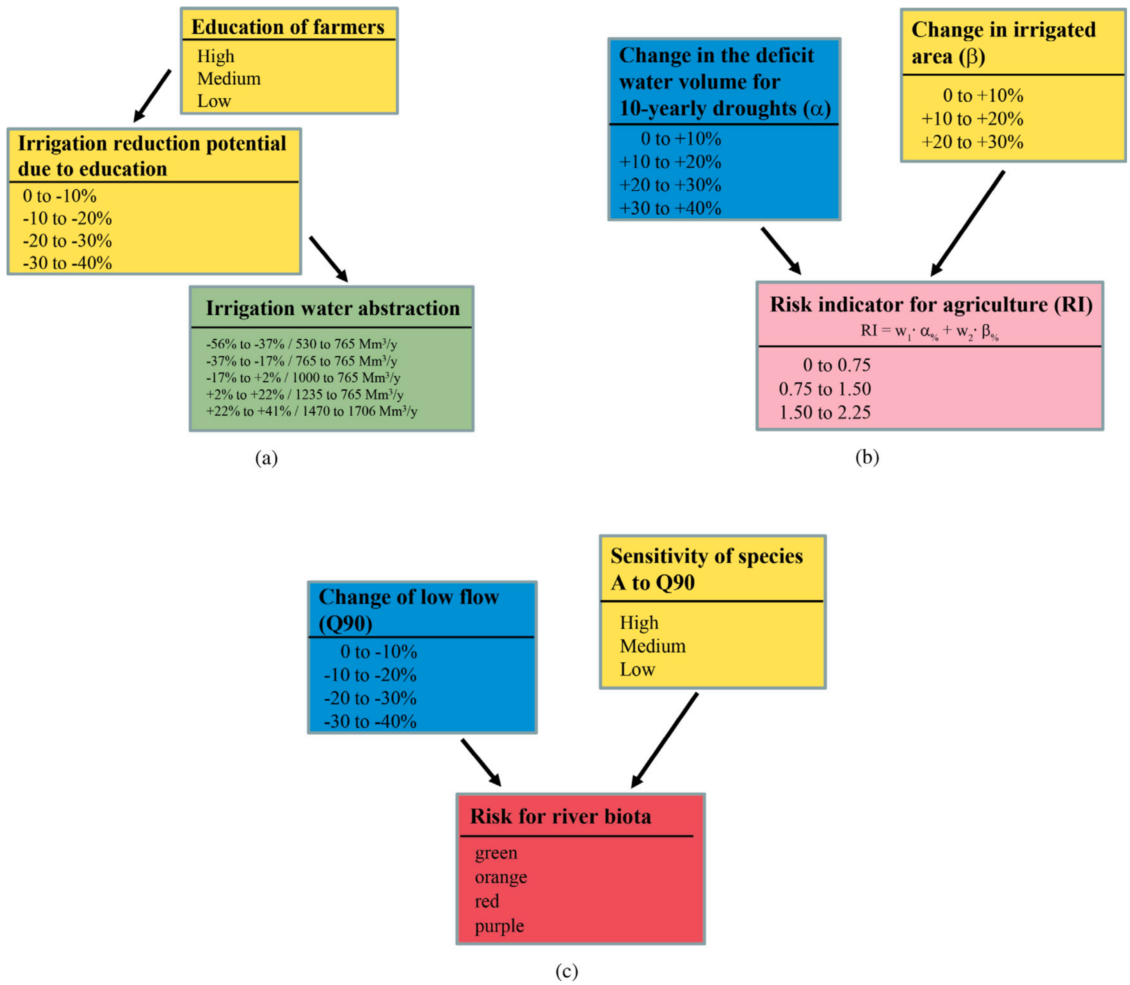


Fig. 12. Integration of qualitative nodes to the co-developed quantitative nodes (a), and two examples to highlight the potential effects of various key risk formulations on setup, i.e., for the risk of changed drought occurrence and deficit volumes to agriculture (b) and the risk of streamflow changes on river biota (c). Each example combines a multi-model ensemble informed hazard (blue) with a vulnerability/exposure (yellow). In the case of (b), the "change in drought water deficit volume" combines with the "change in irrigated area". Here, only relative changes are necessary to compute the risk to agriculture. In the case of (c), the (quantitative classes of) "change of low flow (Q90)" combine with the "sensitivity of species A to Q90" to qualitative node classes in the child (risk) node. Even if hazard and vulnerability differ with respect to units, they can be combined via beliefs in the CPT or via a correlation learned from data.

sensible beliefs, no plausible results can be expected. Thus, awareness of this internalization in the setup is important, and the latter case may have merit in structurally separating and therefore externalizing both aspects in the design process.

6.2. Limitations

Two important limitations for the use of the proposed method are, one, that the calculation with MATLAB is not user friendly for local experts who are unfamiliar with coding, and two, that the Netica software is not available for free. To use the method as proposed would likely restrict the local user community to universities and engineering companies, or an LCCRA process would need to be supported by engineers or scientists familiar with data processing.

To broaden the user base significantly would require availability of specifically pre-processed ensemble data and an extension of the Bayesian Network software to compute quantitative class boundaries from input data and downlink in the model. As discussed above, the examples of more typical belief networks might mean that neither full values nor quantitative class boundaries (in the case of qualitative classes) are necessary, alleviating the pre-processing requirements of coding familiarity favorably, though processing of multi-model output data remains.

Regarding system knowledge, it may be challenging to define sensible critical thresholds between the relevant risk levels quantitatively. However, it will be essential that users know their systems in a way that allows them to estimate these critical thresholds at least for the current situation (i.e., to know what kind of values are problematic in their system) to be able to interpret the changes in the future accordingly.

It should be understood by all participating users that Bayesian Networks, with its simplified system representation through boxes, are not suited for a detailed quantification of the complex water balances in river basins, such as is done in hydrological models. Instead its strength lies in its unique abilities for assessing the local risk of water resources impacted by climate change.

7. Conclusion

The presented approach has the potential to support the many LCCRAs necessary for a successful adaption to climate change worldwide. This study shows how the complex quantitative information of multi-model ensembles about future climate change-driven hydrological changes can be integrated into a Bayesian Network to estimate risks for water supply due to uncertain future climate change and water demand. Using the presented methods, local knowledge about current hydrological conditions and water use as well as local scenarios of future water use can be optimally combined with state-of-the-art estimates of climate change-driven hydrological changes and their uncertainty. These estimates can be derived from the freely available output of global hydrological models and cover all continents of the Earth. This suggests a very wide applicability of our approach for integrating multi-model ensemble output with Bayesian Networks, which is not restricted to freshwater-related climate change adaptation as multi-model ensemble data of the output of other types of global-scale impact models such as agricultural models or biome models is also freely available from ISIMIP (www.isimip.org). Our methodology is applicable for local experts with some experience in coding — working, e.g., in engineering companies or universities. They can download multi-model ensemble data of physical hazards of climate change from data portals and develop a Bayesian Network for their specific region and problem field for LCCRAs.

CRediT authorship contribution statement

Fabian Kneier: Study design, Formal analysis, Data preprocessing with MATLAB, Calculations with Bayesian Network, Methodology, Visualization, Writing draft, Reviewing and editing, Writing final manuscript. **Laura Woltersdorf:** Study design, Data research from literature, Local expert knowledge elicitation, Formal analysis, Calculations with Bayesian Network, Methodology, Visualization, Writing draft, Reviewing and editing. **Thedini Asali Peiris:** Data processing of multi-model ensemble, Visualization, Reviewing and editing. **Petra Döll:** Study design, Supervision, Reviewing and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The study was written in the frame of the project CO-MICC which is part of ERA4CS, an ERA-NET project initiated by JPI Climate, and is funded by BMBF (Germany), BMWFW (Austria) and ANR (France), with co-funding by the European Union (Grant O1LS1709A). We thank Yoshihide Wada, Yusuke Satoh and Peter Burek from the International Institute for Applied Systems Analysis (IIASA) in Austria and Lauren Seaby and Dieter Gerten from the Potsdam Institute for Climate Impact Research (PIK) in Germany for providing their global hydrological model data. The BN roadmap was co-developed by local experts Soumaya Ben Rached, Hamadi Habaieb, Mourad Briki, Abdelouahab Smati, Meriem Alaouri, Fatima Driouech, Asma Bouchkara, Amina Saaidi, Sahabi Abed Salah, Hocine Irekti, Yousri Gafsaoui, Jose Albiac, Jose Cuadrat, Laurent Pouget, Cesar Trillo, Ernesto Rodriguez Camino, Rogelio Galvan Plaza, Luis Miguel Barranco Sanz, Miguel Angel Garcia Vera, Garcia Gomez.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.envsoft.2023.105764.

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